The Implications of Skewed Risk Perception for a Dutch Coastal Land Market: Insights from an Agent-Based Computational Economics Model

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Dutch coastal land markets are characterized by high amenity values but are threatened by potential coastal hazards, leading to high potential damage costs from flooding. Yet, Dutch residents generally perceive low or no flood risk. Using an agent-based land market model and Dutch survey data on risk perceptions and location preferences, this paper explores the patterns of land development and land rents produced by buyers with low, highly skewed risk perceptions. We find that, compared to representative agent and uniform risk perception models, the skewed risk perception distribution produces substantially more, high-valued development in risky coastal zones, potentially creating economically significant risks triggered by the current Dutch flood protection policy.

Key Words: land markets, risk perceptions, agent-based modeling, the Netherlands, survey

Empirical research has established a good understanding of the drivers of land value: spatial factors such as the productive potential of the land, proximity to destinations of interest, and neighborhood amenities and disamenities, as well as characteristics of land market participants, includ-

ing available budgets, relative preferences for spatial factors, and perception of risk. Analytical models effectively demonstrate how these factors contribute to potential land rents, given fairly simple representations of space and a limited diversity of participants in the land market. However, for many real-world problems, the effects of diversity in both land market participants and their spatial environment, and the ways in which individual and spatial diversity interact and feed back to shape the evolution of land rents over time, are central to research questions of interest. Modeling such problems requires innovative new modeling approaches (Irwin 2010).

In this paper, we model a real-world problem with such characteristics, the case of Dutch coastal land markets. Land in the coastal zone is characterized by high amenity values, contributing to its attractiveness for development, and to high levels of flood risk. The extent and value of development in the coastal zone depend on the risk perceptions of those participating in the land market. At the same time, investments in flood-protection infrastructure by the government will be motivated by the economic value of development along the coast. These two factors lead to a potential

upward cycle of coastal development and economic vulnerability. If participants in the land market have a sufficiently low perception of risk, intensive development will occur along the coasts, and land values will be relatively high. These high land values may motivate higher levels of flood protection, leading in turn to reduced risk perceptions and further coastal development.

While most of the Dutch coast is protected by a state-financed system of dikes, certain coastal areas are excluded from public flood protection since their protection is not cost-efficient for society (Rijkswaterstaat 2002). Nevertheless, individuals may invest in these areas at their own risk (Poelmann Commissie 2005, Deltacommissie 2008). Yet, the risk perceptions of Dutch residents remain low, raising the question of how economically vulnerable developments in these unprotected regions might be. This paper presents a model to explore one aspect of this problem: how the risk perceptions of Dutch citizens might shape land development and land values in these unprotected coastal zones. Moving beyond the abstract modeling work presented in Filatova, van der Veen, and Parker (2009), this paper uses survey data to motivate, parameterize, and qualitatively validate our model. Specifically, we focus on how the real-world, highly skewed risk perceptions of market participants affect land market outcomes. We employ an agent-based computational economics modeling approach to tackle this problem, as these models are uniquely suited to explore land market outcomes that are driven by interactions between individual and spatial heterogeneity (Irwin 2010).

The paper proceeds as follows. We first discuss agent-based computational economics as a tool to model complex land market dynamics. Second, as an example of a problem at the frontier of the economics of land use, we discuss the case of land markets in Dutch coastal towns and summarize results of a survey conducted in the Netherlands in 2008. Then, we briefly review conventional economic models that capture effects of spatial amenities and disamenities on land rents and patterns, and we outline the basic mechanisms of our agent-based land market model. Finally, we present and discuss the results of a coastal land market model parameterized using our survey data and provide discussion and conclusions.

Agent-Based Computational Economics for the Economics of Land Use

Agent-based computational economics (ACE) uses simulation methods to study economies as evolving systems of autonomous interacting heterogeneous agents (Axtell 2005, Tesfatsion and Judd 2006). In ACE models, agents individually make decisions based on the state of the environment and their personal preferences and behavioral rules, which in market models are based on microeconomic principles. When a population of such agents interact in the simulation environment, one may observe emergent phenomena or patterns (e.g., price and trade volume, land use patterns, etc.). ACE has been widely applied to a variety of market settings, including financial, electricity, commodity, and labor markets (Epstein and Axtell 1996, Arthur, Durlauf, and Lane 1997, Kirman and Vriend 2001, LeBaron 2006, Marks 2006, Tesfatsion 2006). Often ACE models replace a centralized price determination mechanism (i.e., equilibrium conditions motivated by a story of a Walrasian auctioneer) with decentralized bilateral trading among agents (Tesfatsion and Judd 2006). Due to this flexible model structure, ACE provides a platform for wider exploration of out-of-equilibrium dynamics (Arthur 2006), agent heterogeneity (Kirman 1992), bounded rationality (Simon 1997), and interaction between agents (Axtell 2005).

Economic agents in ACE models are usually heterogeneous, involved in interactions with each other and their environment, boundedly rational, and able to learn and adapt to the behavior of other traders and aggregated market conditions. These aspects of ACE models make them well-suited to the modeling of land markets. As discussed in greater detail in Parker and Filatova (2008), Filatova, Parker, and van der Veen (2009), and Irwin (2010), economic agents operating in land markets (including residential buyers and sellers, developers, and rural landowners) generally have heterogeneous preferences, resources, and knowledge, and the landscape over which land markets operate is characterized by spatially heterogeneous patterns and complex networks. Land market participants have imperfect information when forming expectations about land values because each spatial good has unique characteristics in space and time, and because housing market goods are infrequently purchased. These mar-

ket characteristics limit the applicability of traditional economic tools for modeling land markets. Specifically, analytical urban economic models accommodate agents' heterogeneity only in combination with a 1D landscape (Anas 1990, Epple and Platt 1998, Irwin 2010) and not more than two attributes of the spatial landscape [e.g., distance to Central Business District (CBD) with either amenities or hazard risks]. The main reason for this limitation is that spatial patterns of equilibrium land rents in such models are generally identified through simplifying assumptions regarding individual and/or spatial heterogeneity (for example, that buyer utilities are equated over space) (Parker and Filatova 2008). Spatial econometric models successfully accommodate heterogeneity of the 2D landscape but reflect only a snapshot of a market, as they are estimated using transaction prices, which represent the net results of bargaining between buyers (based on their willingness to pay) and sellers (based on their willingness to accept). This implies that predictions from a regression model based on past transactions may not be robust when underlying behavior or economic conditions change, altering willingness to pay and accept (Bockstael 1996). The statistically estimated demand curve or the probability of choosing a location by a representative agent based on historic data is static, once estimated, while individual location choices may change with time (e.g., because of changing preferences or macroeconomic conditions). ACE approaches to modeling land markets represent a practical and flexible alternative. Irwin (2010) covers these issues in great detail, reviewing literature from multiple disciplines and providing a detailed analysis of the strengths and limitations of traditional economic modeling methods and the potential contributions of agent-based methods. While focused more broadly, Nolan et al. (2009) provides a general introduction to agent-based models for agricultural economists. Schreinemachers et al. (2010) provides another recent review of agent-based models that address spatial and individual-level heterogeneity in an agricultural context.

Motivation and Case Study Data: Dutch Coastal Towns Under Risk

Coastal towns throughout the world are characterized by rich amenities (beaches, coastal view,

etc.) and are often vulnerable to flooding or erosion. Both spatial attributes affect property prices, driving them in opposite directions. Naturally, these positive and negative amenities in coastal towns are spatially correlated (Bin, Kruse, and Landry 2008).

In the Netherlands the coast is protected by a state-financed system of dikes and dunes with estimated flood probability levels of 1 in 10,000 years. Although flood probabilities are believed to be small, due to the high value of developed lands in the dike-protected areas the consequences of a disaster are enormous. The Dutch government uses a concept of "risk"[1] [R in equation (1), known as expected loss in economics] as the main criterion for coastal management (Rijkswaterstaat 2005). In short, if damage costs are high, even a low probability of flooding entails a high level of risk:

$$(1) \qquad R = \text{probability} \times \text{risk}$$

In addition, there are 13 coastal towns in the Netherlands that contain designated "outside-the-dike" areas (see Figure 1a). Each town is divided into two zones: a legally protected one (to the right of the black line in Figure 1b, where probability of erosion/flood is 1:10000 or 1:4000), and a zone where the government does not guarantee any safety level—i.e., an unprotected zone (Rijkswaterstaat 2005). All of the 13 Dutch coastal towns have urban developments in "outside-the-dike" areas, with total potential damage for the unprotected areas of €6.6 billion (Rijkswaterstaat 2005). In October 2005 the Poelmann Commission (2005) published an official recommendation to the government concerning the future of these coastal cities under risk. It advised to allow development in the areas beyond the flood defense line. However, individuals, not the government, should take responsibility for these risks. Given an absence of government regulation (and a lack of availability of private or public flood insurance), market forces will determine the spatial pattern of development and accompanying land rents. Consequently, the total risk in these coastal towns will depend on individual decisions in the land market. However, there is a concern that individuals

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[1] EU water management has used this notion of risk ≠ probability for at least 10 years. Throughout this paper, by *risk* we mean *probability × effect*.

Figure 1a. Risk Towns, i.e., Coastal Cities with Outside the Dike Areas

Figure 1b. Flood Defence Line (Kernzone) That Divides a City into the Legally Protected and Unprotected Zone

Source: Rijkswaterstaat (2005).

are largely unaware of the risks involved (Bočkarjova, van der Veen, and Geurts 2008, Krywkow, Filatova, and van der Veen 2008, Terpstra and Gutteling 2008). These circumstances raise an important policy question: how will the risk perceptions of participants in Dutch coastal land markets affect the degree of land development, the value of developed lands, and the consequent degree of flood risk?

In order to provide data to inform investigation of this question, a household mail survey was conducted in February 2008 in the Dutch province of Zeeland (Krywkow, Filatova, and van der Veen 2008). This province experienced the most severe damage during the last coastal flood, in 1953, and it includes a coastal town that contains outside-the-dike areas. Among other goals, the survey sought to elucidate individual perceptions of flood risk and factors affecting individual location choice. The respondents were asked, on a 1 to 5 scale, "How worried are you that flooding can affect you?" Following Slovic et al. (2004) and Raaijmakers, Krywkow, and van der Veen (2008), this "worry" variable is taken as the indicator of individual risk perception. Figure 2 shows the frequency of distribution of opinions among the 436 respondents.

Figure 2 demonstrates that the level of worry among individuals is dispersed (mean of 2.31, sd = 1.05), and the peak of the distribution is skewed to the left, meaning that the majority of people have a very low level of concern regarding
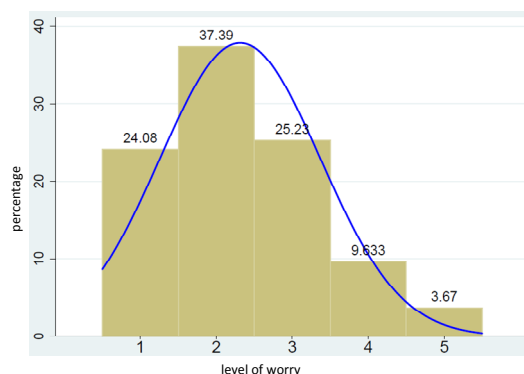

Figure 2. Distribution of Individual Level of Worry That Flooding Could Affect Respondent Personally (1 = do not worry at all, 5 = worry very much)

flooding, in spite of the fact that 25.5 percent of the respondents had personal experience with the 1953 flood, with some suffering financial damage or causalities in their families. Only 2.8 percent of respondents believe that a severe flood is likely to occur in the future, and 91.8 percent are not prepared in the case of a disaster. Other survey questions elucidated that 68.7 percent of respondents consider government responsible for providing safety and that 77.3 percent of the sample consider technical measures (dikes) as the best flood defense measure (Krywkow, Filatova, and van der Veen 2008). In short, current Dutch residents have a high degree of confidence in the ability of the dike system to protect them against flooding—even potentially for some areas where that protection is not ensured by the government.

The survey also studied the importance of various factors for location choice (proximity to the employment center, environmental amenities, and flood safety). Figure 3 reports that time and distance to work are the two most important factors. Many people also considered environmental amenities, including coastal amenities, to be an important factor. Safety from flooding is the least important factor for Dutch people in their location choice. This means that an average respondent might settle in the flood-prone area along the coast if it provides coastal amenities, since the importance of the latter is higher than safety.
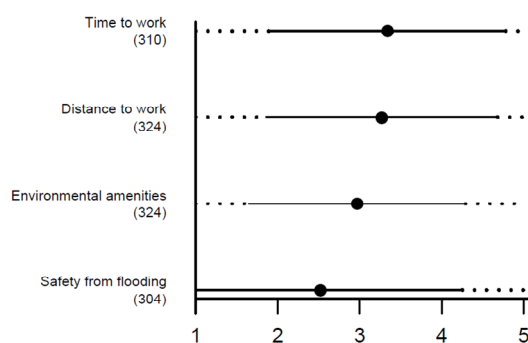

Figure 3. Importance of Different Factors for People Buying a House

Notes: X axis: 1 = absolutely not important, 5 = extremely important. A number in brackets along the Y axis is the number of observations. A circle symbolizes the mean value, the solid line shows standard deviation, and a dotted line connects min and max values.

In addition, the survey used a contingent valuation (CV) approach to elucidate respondents' perceived monetary value of coastal amenities and safety from flooding attached to location.[2] The CV method was used to value both environmental amenities (Alberini et al. 2005) and flood risk (Shabman and Stephenson 1996). Although often hedonic price techniques are used to estimate the contribution of spatial attributes to property values, a CV approach was more practical in this case. First, since coastal flooding in the Netherlands is rare, it is very unlikely that housing prices in the past have integrated flood risk. However, risk perception and willingness to pay for flood protection might have risen following Hurricane Katrina. Second, since the implementation of the Poelmann Commission recommendation was still under discussion, there were no actual transaction data for the outside-the-dike areas under new policy.

Survey respondents were asked to state how much more they would be willing to pay for a house that (i) has a seaside view and (ii) is located in a safe[3] zone, compared to a similar €200,000 house (the average in the province) that (i) has no view and (ii) is located in a risky zone. The majority of respondents, 78 percent of whom were homeowners, stated that they were willing to pay a positive amount for each locational attribute, while about 17 percent of the sample were indifferent (Table 1).

For further analysis we consider only positive willingness to pay (WTP) statements, excluding the "protest" responses. The mean value of the two WTP measures are reported in Table 2 for four groups: (i) all in sample, (ii) respondents who had coastal flood experience (FE) in the Netherlands, (iii) those who had flood experience elsewhere, and finally (iv) those who did not have any flood experience.

As seen in Table 2, the average WTP value for each locational attribute (coastal amenities and safety from flooding) is almost the same as its standard deviation. This diversity in responses

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[2] While these CV estimates were not used to parameterize our land market model for reasons discussed in detail in Filatova (2009), they motivated the structure of our model of buyer's bidding behavior and provide a benchmark for qualitative validation of model results.

[3] The survey did not use specific probabilities but rather used qualitative definitions of safe (i.e., protected by the government) and risky (outside-the-dike) area.

Table 1. Percentages of Respondents Answering the WTP Questions (n = 436)

Variable (n = 436)	Negative Payment	Zero Payment	Positive Payment	No Answer
WTP for coastal amenity	5.05%	17.2%	63.99%	13.76%
WTP for safety	3.9%	16.97%	66.51%	12.61%

Table 2. The Mean WTP

Variable	All	With Flood Experience in the NL	With Flood Experience Elsewhere	No Flood Experience
WTP for coastal amenity	44,229 (30782 / 279)	46,713 (31994 / 143)	47,046 (28739 / 44)	39,709 (28713 / 103)
WTP for safety	47,069 (30018 / 290)	47,273 (30378 / 143)	54,444 (29885 / 54)	44,151 (29110 / 106)

Note: Notation is mean (sd / n).

might have been caused by differences in individual preferences for coastal amenities and individual beliefs about the actual risks associated with flooding. However, regressions modeling WTP for safety found both the level of worry and an income proxy to be significantly positively correlated with WTP, as theory would predict (Filatova 2009).

These micro-level survey data provide some insights about individual location decisions that may be used to explore land market dynamics in coastal towns. Below, we briefly review other approaches to parameterizing ACE decision models and provide additional details on our model parameterization.

Land Market Agent-Based Model and Survey Data

Given that ACE is a fairly new field, protocols for parameterizing agent decision models with real-world data have not been fully codified. Strategies for empirical parameterization depend on the modeling methods, the goal of the modeling effort, and the quality of available data. In contrast to the process of parameterizing environmental processes, which usually follow well-established physical laws, it is less straightforward for a modeler to describe the process of human decision making and to empirically parameterize agents (Berger and Schreinemachers 2006, Robinson et al. 2007). Due to their bottom-up nature, empiri-

cal agent-based models (ABMs) require disaggregated micro-level data about agents' characteristics and/or agents' behavior. Micro-level data can be obtained either by observing decision making of a land-user in a controlled environment (Duffy 2006), from interviews and participatory workshops with stakeholders (Barreteau, Bousquet, and Attonaty 2001), or by gathering survey data (Fernandez et al. 2005, Brown and Robinson 2006). Often, decisions must be made regarding how to incorporate qualitative survey information into the formal rules of the model. ACE models in marketing (Bonabeau 2002) and financial markets (Hommes 2006) frequently use the extended micro-information about individual market decisions (easily available for such markets) in ABMs. Due to the costs of micro-level information acquisition and other challenges (Berger and Schreinemachers 2006, Haase et al. 2008), still few land-use ABMs currently use individual-level survey data.

For our model, the relative importance of spatial characteristics from the survey is used to motivate the structure of the utility function in our model parameterization. We translated the qualitative level of worry that an individual has about potential negative effects of flooding into a quantitative distribution of perceived damages from flooding, making the assumption that worry regarding flooding could be associated with perceived flood damages. This parameterization allows us to create a model to answer the question: What patterns of location and land value might

emerge from buyers with this real-world distribution of flood risk? We assess the results of our modeling effort by examining whether our modeled WTP and land transactions, given implemented decision structure based on stated levels of risk perception from the survey data, are consistent with the WTP estimates obtained from the survey data. This assessment provides qualitative validation of the success of our model, on the assumption that a model parameterized with empirical behavioral rules should replicate empirical behavior.

The ALMA-C Model

Economic agents in a coastal land market face trade-offs between a high amenity waterfront with flood risk and a lower coastal amenity level in exchange for higher safety. To explore urban land rents and land pattern dynamics for the population of agents with skewed distribution of perceived risk, we have developed a two-dimensional urban agent-based land market model (ALMA). Since ALMA has been already extensively described (Parker and Filatova 2008, Filatova, Parker, and van der Veen 2009, Filatova, van der Veen, and Parker 2009), we provide only a brief description here, highlighting the assumptions and features most relevant for this application.

Building Blocks: Conventional Spatial Economic Models

Many of the individual elements affecting location decisions in coastal towns have been modeled individually using analytical approaches. Wu (2001) modifies a 2-D monocentric urban model to include coastal amenities, using a budget-constrained utility maximization model based on amenity and proximity values. MacDonald, Murdoch, and White (1987) and Frame (1998) model location choice in a flood-prone area as a constrained expected-utility maximization problem using an aspatial model with discrete flood risk. Tatano, Yamaguchi, and Okada (2004) similarly model location choice in a city where disaster risk is present, and include potential bias in households' perception of disaster risk. Thus, the standard urban economics model of Alonso (1964) has been extended to account for either environmental amenities or natural hazard risk, but not

both simultaneously in a spatially explicit model. To our knowledge, it is not possible to incorporate both the three sources of spatial heterogeneity (distance to CBD, flood risk, and coastal amenities) and the agent heterogeneity (e.g., risk perceptions) in an analytical equilibrium model, as discussed earlier.

Agent-Based Land Market Model

The ALMA model for the coast (ALMA-C) simulates the emergence of urban land patterns and land rents as a result of bilateral interactions between buyers and sellers of land with application to a coastal city. ALMA-C borrows much from analytical monocentric urban models (including trade-offs between travel costs to the CBD and land rent, the fact that land is allocated to the highest bidder, and utility dependent on amenities and distance to the CBD) and an expected utility approach. Differences show up in the direct modeling of price formation, the heterogeneity of both agents and the spatial landscape, and the simulation approach used to derive a market equilibrium. Similarly to other abstract models of its type, ALMA-C does not strive to represent all driving factors of land-use change that might be included in a fully empirical model designed for landscape projection and scenario analysis. Rather, it is a stylized model designed to illuminate empirically motivated, but abstract, outcomes. Thus, although factors identified as most important for housing choice in our study area are included, some factors, such as housing characteristics and public amenities, are excluded to best focus the model on the research question of interest. Further, the model operates over an abstract landscape and, consistent with other models of its type, the model is initialized with the assumption that all properties are available for sale, in order to avoid artifacts due to initial landscape patterns.

Spatial landscape. All three experiments discussed in this paper were performed on the landscape of 35 by 63 cells, initialized with 1,890 buyers and 1,890 sellers. Since in equilibrium the model is essentially an open city model, some buyers may choose to not purchase a property, meaning that the number of converted cells and thus the size of the city will vary between experiments. Each cell is assumed to represent a

single property differentiated by distance (D_{cbd}) from the CBD (which is normalized by landscape size to an inverse measure *Prox*, in order to control for the size of the landscape), the level of coastal amenities (A) (estimated as a normalized distance to the coast), and an objective probability of flooding or erosion (PF_{obj}) that is a function of distance to the coast D_{coast}. The probability of flooding is fairly constant close to the coast, then falls off abruptly at a given distance, in order to qualitatively represent the "outside-the-dike" areas (see Figure 4, top graph) in Dutch coastal towns discussed above. The exact equations describing estimation of spatial attributes can be found in Filatova, Parker, and van der Veen (2009) and Filatova, van der Veen, and Parker (2009).

The land market. Following an ACE approach, the centralized price determination mechanism of the standard analytical model is replaced by a set of bilateral trades in ALMA. At initialization, all land is assumed to be under agricultural use (i.e., each cell is occupied by a seller with the reservation price equal to the price of agricultural land), and the CBD is exogenously set as in the Alonso model. Market interactions start when sellers announce their ask prices and buyers enter the market to search for the best deal and start submitting their offer-bids, purchasing only one property. A seller collects all possible bids and selects the highest, if any. A trade occurs if the highest bid is above the seller's ask price. The final transaction price (i.e., land rent) is an arithmetic average of the ask price and the highest bid price. Successful buyers and sellers then leave the market, with unsuccessful buyers assumed to locate elsewhere per the open city assumption. The model continues in the next round with an updated landscape and an updated (lower) number of buyers, sellers, and properties on the market until all the gains from trade are exhausted. At this point, the land market has essentially reached an equilibrium where no buyer or seller has an incentive to engage in additional trading.

Buyers' behavior. Buyers search for the location that maximizes their expected utility [equation (2)] and is affordable under their disposable budget for housing net of transport costs (Y). The Dutch survey showed that proximity to work and environmental amenities are the most important factors that affect individual location choices. Al-
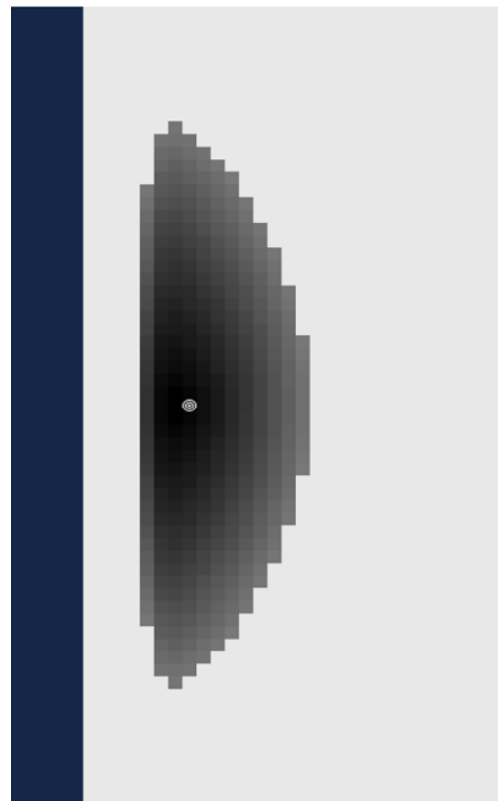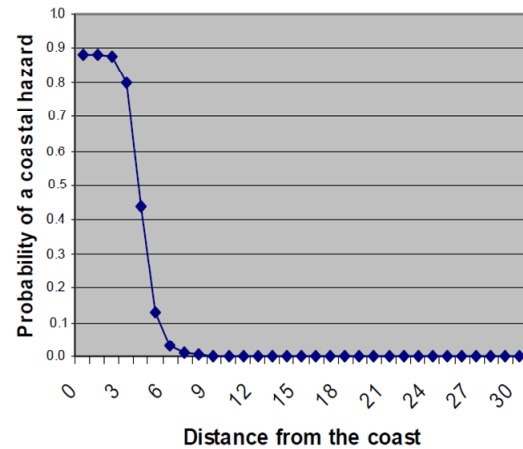

Figure 4. Function of the Probability of a Coastal Hazard as a Distance to the Coast (top graph) and Land Rent Patterns, Experiment 1 (homogeneous agents parameterized with the mean value from the survey) (bottom graph)

though other factors are likely to affect bids, including them here would complicate model analysis and results without adding new insights rele-

vant to our case study. Thus, α and β in the utility function denote individual preferences for coastal amenities and proximity correspondingly:

$$(2) \qquad U = \alpha \times \ln(A) + \beta \times \ln(Prox)$$
$$E(U) = PF \times U \times (1 - C_{dam}^i) + (1 - PF) \times U,$$

where $C_{dam}^i \in [0,1]$ is a damage coefficient denoting the loss from flood or erosion as perceived by an agent *i*, and *PF* is the probability of flooding. The distribution of survey responses regarding worry about flood risk is used to parameterize the coefficient C_{dam}^i in equation (2). Note that the level of worry in Figure 2 varies from 1 to 5 and the damage coefficient varies from 0 to 1. Thus, the distribution is normalized through translation to a scale from 0 to 1, implying that the average damage coefficient is now 0.33.

A buyer identifies the property that gives her maximum utility and forms her WTP for the property. In an analytical model, an economic agent maximizes her utility by finding the optimal combination of housing and non-housing goods under her budget constraint. In the absence of an equilibrium price determination mechanism in the agent-based model, it is not possible to solve a budget-constrained utility maximization problem, because market-clearing assumptions are needed to solve for the price of housing in the budget constraint. [See Parker and Filatova (2008) and Filatova, van der Veen, and Parker (2009) for discussion, and Ettema (2011) and Magliocca et al. (2011) for examples of a price expectation mechanism that could be used to determine an expected purchase price for a property.] To allow for out-of-equilibrium price determination, we construct a WTP function that reflects the assumption of weak separability of the housing and non-housing goods. Specifically, a buyer's WTP is a function of her expected utility $E(U)$, her individual budget net of travel costs (Y), and the prices of all other goods (the influence of which is expressed by a constant *b* that determines the convexity of the WTP for housing):

$$(3) \qquad P_{WTP} = \frac{Y \times E(U)^2}{b^2 + E(U)^2}.$$

Thus, there is substitutability between housing and non-housing goods (a buyer agent will spend part of her budget on housing and transport, but there will be some residual that she is assumed to spend on non-housing goods). This function behaves qualitatively as a conventional demand function (Filatova, Parker, and van der Veen 2009). In this paper, buyers' bid price is equal to their WTP [Filatova (2009) explores effects of bid prices that deviate from WTP depending on market conditions]. Having identified their desired property and bid price, buyers submit their offer-bids to the sellers.

Sellers' behavior. The ask price of a seller is equal to his reservation price, which is assumed to represent the agricultural land reservation price (P_{ag}). In other papers we presented more advanced pricing strategies of sellers, allowing them to attempt to maximize their gains from trade (Filatova, Parker, and van der Veen 2009, Filatova, van der Veen, and Parker 2009).

Results

We run three sets of experiments, each having a different parameterization for the perceived individual damage coefficients across the population. In the first set of experiments, buyers have homogeneous damage coefficients equal to the average survey value (C_{dam}^i = 0.33). The second set of experiments is performed with buyers whose perceived damage coefficients are parameterized using the normalized distribution of "level of worry" from the survey data, as described above. Note that distribution of damage coefficients in the second case is skewed to the left, as in the survey results. In the third set of experiments, buyers' damage coefficients are drawn from a uniform distribution ranging between zero and one. In summary, experiments 1 and 3 provide hypothetical baselines (a representative agent approach, based on the real-world mean, and a case of maximum dispersion of risk perceptions) for comparison to the real-world distribution of agent risk perceptions.

The aggregated results of the ALMA-C simulations are spatial patterns of urban development, spatially explicit land-rent patterns (i.e., realized land transaction prices—the average of the ask price and the bid of the buyer with the highest valuation for the land—at different distances from the city center), and a set of economic and spatial metrics (bid price and land rents, urban

size, and urban extent). In addition, we estimate land-rent gradients for each experimental outcome, using simulated transaction data, in the tradition of spatial econometrics. Land-rent gradients are common measures used both in analytical and empirical models (see Anas, Arnold, and Small 1998). Often they are constructed to test the degree to which actual urban areas resemble the spatial structure of a monocentric model (Bell and Irwin 2002). Traditionally, analytical rent gradients have been derived from theoretical models, and these have been compared to rent gradient functions separately estimated from real-world data. The two modeling methods have remained disconnected, however, since the theoretical models do not produce the spatial patterns of heterogeneous land rents, linked to the heterogeneous attributes of the successful bidder, that are used to estimate the real-world functions. ABM methods can uniquely produce simulated data, generated by a theoretical model, in the same structural form as the empirical data. The regression-based land-rent gradient estimates, therefore, provide a more direct link between theoretical and empirical models than was previously possible.

In all three experiments discussed in this paper, residential buyers are homogeneous with respect to their preferences for coastal amenities, proximity to the CBD, and incomes. The only difference between the three experiments is the distribution of individual damage coefficients of agents. The model parameters used in the three experiments are listed in Table 3. Each experiment run was performed 30 times to avoid random number biases, although, in practice, output values differ very little between model runs. Summary tables report average values across model runs. Rent gradients are estimated using pooled data from all model runs.

EXPERIMENT 1. *Agents with a homogeneous coefficient of perceived damage equal to the mean value of the survey sample*.

Experiment 1 essentially employs the representative agent traditional for the conventional analytical model. The top part of Figure 4 shows the graphical form of the probability of natural hazard function, which is a function of distance from the coast. Its horizontal axis matches the map below. The bottom part of Figure 4 shows the rent patterns of the realized transactions. The dark area on the left represents the ocean and the white circle in the middle is the CBD. The intensity of gray color symbolizes the value of land: the darker the color, the higher the land rent. The light-gray area represents the rural-urban fringe. The results verify theoretical expectations in the case of homogeneous, risk-averse buyers who value coastal amenities. Land rents decrease with the distance from the CBD, but are higher in the direction of the coast. There are no developments in the immediate proximity to the coastline: agents' expected utility there is too low to outbid sellers' reservation prices, given the flood risk. Note, this occurs even though the average buyers represented in this model perceive a low level of risk.[4] We call the line at which the city's left seawards border stops the "safety contour" as a point of reference for the following experiments (Table 4).

We estimate a functional representation of the model's rent gradient, using a regression with the model-generated land rents as our dependent variable, and the two spatial variables—distance to the CBD and distance to the coast—as independent variables. A cubic regression model provided an adequate model fit ($R^2 = 0.98$, Table 5).

Figure 5 presents a 2D cross-section of the city land values along the perpendicular connecting CBD to the coast. The Y axis represents the value of a spatial good, and the X axis represents distance to the coast. The distance to the CBD (situated 8 spatial units away from the coast) can be directly translated into distance to the coast (using $D_{CBD} = |D_{coast}-8|$) [see Filatova, van der Veen, and Parker (2009) for more details]. The estimated rent gradient for Experiment 1 is plotted in the solid curve in Figure 5. It peaks at the CBD (the right dotted line) and decreases seawards because all agents perceive uniformly high risk (their coefficient of perceived damage is equal to the mean value of the survey sample). Developments do not expand beyond the safety contour (the left dotted line). This rent gradient, again, reflects the valuations that would be obtained from a representative agent model, i.e., one that imposed an assumption of buyer homogeneity.

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[4] This outcome is a result of our particular model parameterization, chosen to create an appropriate baseline for our case study; alternative parameterizations are possible that would produce higher levels of development and land values toward the coast.

Table 3. Values of Parameters in the Simulation Experiments

Symbol	Meaning	Experiment 1	Experiment 2	Experiment 3
Y	Individual budget	800	800	800
P_{ag}	Price for agricultural land	200	200	200
TCU	Transport costs per unit of distance	1	1	1
b	Constant in equation (3)	70	70	70
α	Individual preference for green amenities	0.6	0.6	0.6
C_{dam}^i	Flood damage coefficient	0.33	Survey distribution	Uniform distribution [0-1]
avC_{dam}	Mean C_{dam} in the buyer population	0.33	0.33	0.5

Table 4. Economic and Spatial Metric Outcomes of the ALMA-C Experiments

	Experiment 1	Experiment 2	Experiment 3
Bid price, mean	212.46	215.61	213.33
Bid price, sd	7.87	9.74	8.66
Land rent, mean	206.23	207.81	206.67
Land rent, sd	3.94	4.87	4.33
Total property value in the city, mean	82492.08	129256	110841.6
Total property value in the city, sd	0	20.07	1322.52
City size (urbanized cells), mean	400	622	536.33
City size (urbanized cells), sd	0	0	6.39
City border (extensive margin), mean	22.02	26.93	23.58
City border, (extensive margin), sd	0	0	0.68
Urban cells seaward from safety contour, mean	0	204	121.9
Urban cells seaward from safety contour, sd	0	0	6.38
Total property value seaward from safety contour, mean	0	42913.45	25267.48
Total property value seaward from safety contour, sd	0	0	1316.47

EXPERIMENT 2. *Agents with heterogeneous coefficients of perceived damage parameterized using the survey data*.

To review, the difference between Experiment 1 and Experiment 2 is that a representative agent with a damage coefficient equal to the mean value of the survey sample is replaced by a heterogeneous population of agents initialized with the empirical distribution of "worry." The average perceived damage coefficient of the heterogeneous agents is equal to the mean value of survey data, i.e., the damage coefficient in Experiment 1. Thus, buyers are the same on average. Comparing outcomes from Experiments 1 and 2 allows us to examine how accounting for the real-world heterogeneity of buyer's risk perceptions affects patterns of urbanization and land values.

Average bid prices and consequently land rents in Experiment 2 are a bit higher than in Experiment 1 (see Table 4). Buyers in the population that have low perceived damage coefficients will perceive even lower risk than the representative,

Table 5. Cubic Regression of Simulated Land Prices

	Experiment 1	Experiment 2	Experiment 3
R^2	0.9776	0.9886	0.8457
Intercept	181.26 (0.28 / 644.93)	221.6 (0.12 / 1862)	213.59 (0.4 / 536.97)
D_{am}	10.58 (0.08 / 141.03)	-0.58 (0.03 / -20.49)	2.12 (0.09 / 22.93)
D^2_{am}	-1.02 (0.01 / -150.82)	-0.03 (0 / -12.65)	-0.26 (0.01 / -30.84)
D^3_{am}	0.03 (0 / 136.76)	0 (0 / 5.27)	0.01 (0 / 18.3)
D_{cbd}	-0.79 (0.03 / -23.31)	-0.63 (0.02 / -29.9)	-0.84 (0.07 / -11.45)
D^2_{cbd}	0.0184 (0.002 / 9.95)	0.0048 (0.001 / 38.7)	0.0232 (0.004 / 50.57)
D^3_{cbd}	-1.00E-04 (0 / -2.35)	-4,00E-04 (0 / -158.2)	-4,00E-04 (1.00E-04 / -42.7)
$D^2_{am} \times D_{cbd}$	0.0021 (0 / 10.51)	-4,00E-04 (1.00E-04 / -41.7)	0.001 (3.00E-04 / 32.75)
$D_{am} \times D^2_{cbd}$	-0.003 (0 / -24.63)	-3,00E-04 (1.00E-04 / -43.1)	-0.0027 (3.00E-04 / -97.81)
$D_{am} \times D_{cbd}$	0.0172 (0.005 / 3.58)	0.0109 (0.003 / 3.97)	0.0204 (0.009 / 22.03)
C_{dam}	NA	-331.749 (0.306 / 1082)	-689.09 (0.98 / 700.39)
C^2_{dam}	NA	83.897 (0.449 / 186.68)	616.28 (15.33 / 402.1)
C^3_{dam}	NA	-0.6994 (0.275 / -27.158)	-154.06 (10.67 / 144.3)
$C_{dam} \times D^2_{am}$	NA	-0.2097 (0.003 / -749.4)	-0.2262 (0.008 / 271.3)
$C^2_{dam} \times D_{am}$	NA	-0.6245 (0.028 / -221.53)	-28.641 (0.099 / 289.3)
$C_{dam} \times D^2_{cbd}$	NA	0.0112 (9.00E-04 / 125)	0.0203 (0.003 / 70.57)
$C^2_{dam} \times D_{cbd}$	NA	-0.0618 (0.015 / -4.24)	-0.802 (0.053 / 150.9)
$C_{dam} \times D_{am}$	NA	54.179 (0.053 / 101.75)	76.882 (0.16 / 478.03)
$C_{dam} \times D_{cbd}$	NA	-0.1524 (0.023 / -65.81)	0.2684 (0.076 / 35.11)

Note: Notations are as follows: estimate (st.error/t-value); D_{am} is distance to the coast; D_{cbd} is distance to the CBD; C_{dam} is individual coefficient of perceived damage.

agent in Experiment 1, whose damage coefficient is already skewed to the left. Thus, these economic agents value land in the flood-prone zone quite highly (because the proximity of coastal amenities is present and their flood risk perception is low or zero). As a result, spatial patterns in
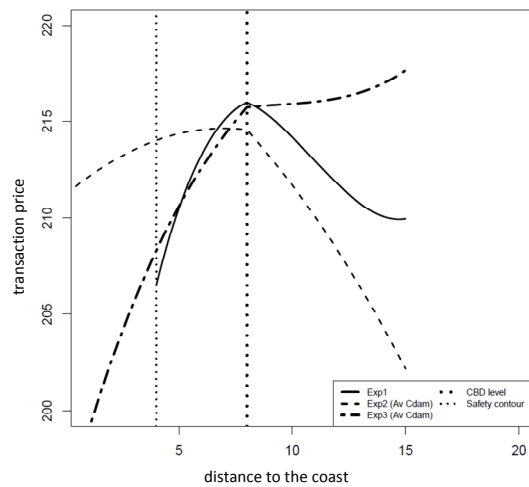
Figure 5. 2D Cross Section of Rent Gradient

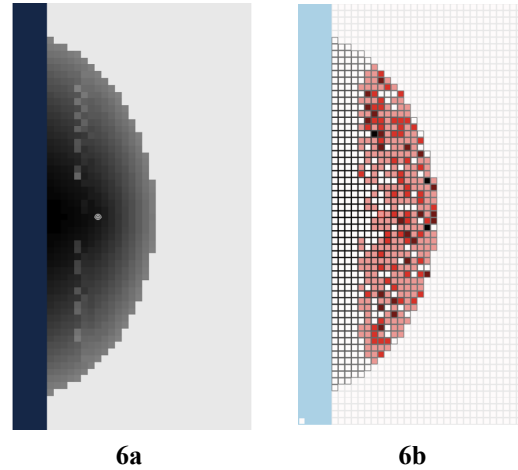6a   6b

Figure 6. Results of Experiment 2 (heterogeneous agents parameterized with empirical survey data): Land Rent Pattern (6a) and Map of Perceived Damage Coefficients of Agents Settled in the City (6b)

Note: In graph on right, the white color means $C_{dam} = 0$, the darkest color means $C_{dam} = 1$.

Experiment 2 differ significantly from Experiment 1, in spite of the fact that micro-attributes of agents in two experiments are the same on average. In contrast to Figure 4, almost all the area along the coastline in Figure 6a is urbanized. On average about 204 cells are converted into urban use in the zone seaward from safety contour, leaving 33 percent of the total property value in this coastal city under risk (Table 4). Total property value in the city increased by 57 percent compared to Experiment 1. This is due to the increase in the bid price of agents with low risk perception who were willing to buy property at the coast, attracted by rich coastal amenities. When bid prices rose above the agricultural land price, more land was converted at the seaward border of the city, leading to a 56 percent increase in city size (where 51 percent is beyond the safety contour and 5 percent is at the outer border).

Figure 6b shows the spatial distribution of agents' perceived damage coefficients. This figure illustrates a unique advantage of agent-based modeling: its ability to produce fine-scale information regarding spatial and individual-level heterogeneity. This visualization confirms that the model is operating as expected (structural validation), and it further provides a potential target for empirical validation, in cases where spatially explicit survey data are available. Notably, the most seaward area where the probability of flooding or erosion is significant (see upper part of Figure 4) is occupied by agents with the lowest perceived

damage coefficient, $C_{dam} = 0$. At the same time, agents with higher C_{dam} (darker color in Figure 6b) settle more landward. This sorting is an emergent model outcome, since it is a result of a land market allocation. Specifically, agents with $C_{dam} = 0$ have much higher expected utility along the coast compared to agents with $C_{dam} > 0$. Thus, the former bid more for coastal properties than those with higher levels of worry about potential coastal risk.

One can also observe that, in spite of the fact that agents are heterogeneous, the land rents over most of the landscape appear as if there were homogeneous agents operating in the land market (Figure 6a). There is dispersion in land rents only in the area bordering the safety contour. Although this may seem counterintuitive given the model structure, the result can largely be explained by the distribution of risk perceptions. This result emerges due to the form of the buyers' risk perceptions (highly skewed to the left, with a reasonably high proportion of zero values) and the skewed, almost discrete form of the hazard probability function. Buyers are heterogeneous only with respect to their coefficients of perceived damage, so differences in their bids for land occur only due to differential risk perceptions. The

market then allocates agents with zero damage coefficients seawards from the safety contour (Figure 6b). The majority of these buyers perceive no risk, creating a zone of land rent patterns essentially produced by homogeneous buyers, who bid as if there were no flood or erosion risk disamenity associated with this land. Landwards from the safety contour, there are buyers who are heterogeneous with respect to their perceived damage coefficients (Figure 6b). However, since the actual hazard probability is approaching zero in this area (upper part of Figure 4), this spatial landscape is essentially homogeneous with respect to flood/erosion risk, so heterogeneous damage perceptions do not affect land rents. There is only a narrow strip of land in immediate proximity to the safety contour where the actual probability of flooding/erosion is still significant, and where agents with non-zero coefficients of perceived damage find it economically attractive to locate.

One of the advantages of agent-based market simulations is that agent-level characteristics can be recorded and analyzed together with market transaction data, providing more detailed data than often is available in the real world. Although this is model-generated data, not empirical, it allows us to control for potential effects of heterogeneity in individual preferences and perceptions in our rent gradient estimates—and therefore to understand the theoretical effects of the individual level factors, even if we lack access to these data in a real-world context. Following Filatova et al. (2009), we econometrically estimate a rent gradient function for Experiment 2 using three explanatory variables: two spatial attributes (distances to the coast and CBD) and agents' individual coefficients of perceived damage (Table 5). The estimated land gradient from Experiment 2 (dashed curve), plotted using mean values for the buyer's characteristics in Figure 5, behaves differently than the solid curve showing the estimated land-rent gradient of data from Experiment 1. It not only remains above the reservation price beyond the safety contour, but the dashed curve is also much higher than the solid one to the left of the CBD towards the coast, meaning higher land rents in the area beyond the safety contour and, consequently, higher direct potential damage in the case of a hazard—all resulting only from the empirically parameterized heterogeneity among

agents. This highlights the importance of using the real-world distribution of risk perceptions, rather than taking a representative agent approach.

EXPERIMENT 3. *Agents with heterogeneous coefficients of perceived damage parameterized using uniform random distribution.*

In Filatova, van der Veen, and Parker (2009), we highlight the importance of individual heterogeneity for the outcomes of a land market. Realizing difficulties in obtaining such data, we proposed that researchers and policymakers should at least use a random distribution to explore the results of hypothetical agent heterogeneity. In Experiment 3, we compare the results from Experiment 2 to an outcome in which we assume that the actual distribution of buyer risk perceptions is unknown, but can be proxied by a uniform distribution. This case could also be viewed as one in which people have no information about potential flood risk and make a random prediction regarding potential risks.

As seen from comparison of Figures 7a and 6a, the spatial morphologies of the two estimated cities differ, with the uniform distribution producing a smaller city. The city border has shrunk by 12 percent and the urban population has decreased by 14 percent (Table 4). The number of urban cells seawards from the safety contour is approximately half the number urbanized in Experiment 2. The proportion of total property value under risk is 23 percent of the total value in the Experiment 2 city, compared to 33 percent in Experiment 2. As before, this occurs because more land is converted into urban use than in Experiment 1 (i.e., agents who underestimate coastal risks have high enough valuations of land along the coast to outbid the reservation price of sellers). Since average risk perceptions are higher in Experiment 3 than Experiment 2 ($avC_{dam} = 0.33$ vs. $avC_{dam} = 0.5$, Table 3), it might not be so surprising that a balanced uniform distribution causes fewer developments in the risky zone compared to a left-skewed distribution of worry. Nevertheless, other studies report that a uniform distribution provides the upper bound of variation of aggregated outcomes compared to parameterization with survey data (Brown and Robinson 2006). We expect that the difference in our model results comes from the fact that our model implements a formal land market with competitive
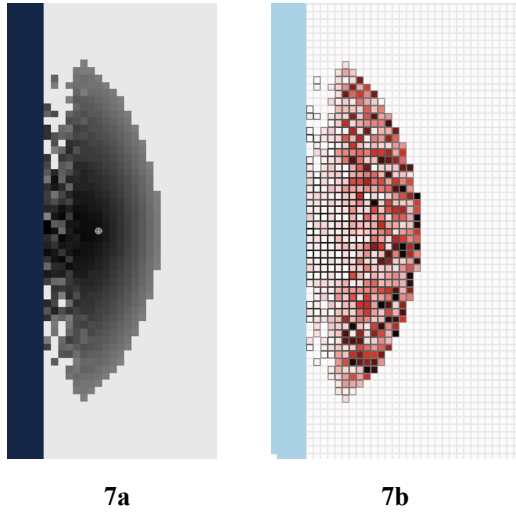
7a   **7b**

Figure 7. Results of Experiment 3 (heterogeneous agents parameterized with uniform distribution): Land Rent Pattern (7a) and Map of Perceived Damage Coefficients of Agents Settled in the City (7b)

Note: The white color means $C_{dam} = 0$, the darkest color means $C_{dam} = 1$.

bidding (rather than only demand-driven allocation), which alters final land development patterns. Work in progress will allow us to formally test this hypothesis (Parker et al., forthcoming).

Experiment 3 leads to more urban expansion than Experiment 1, however, in spite of the fact that the average risk perception for Experiment 3 ($avC_{dam} = 0.5$) is higher than Experiment 1 ($avC_{dam} = 0.33$). Again, in Experiment 3 urbanization spreads into the risky zone because the buyers with lower than average ($C_{dam} = 0.33$) risk perceptions drive market outcomes beyond the safety contour. These buyers simply do not exist in the market in the representative agent model in Experiment 1.

In this experiment, buyers who, through market sorting, have settled seawards of the safety contour have very low, but still heterogeneous damage coefficients. (Compare light gray color of cells along the coast in Figure 7b to the white color in Figure 6b). As a result, land rents are heterogeneous along the coast in Experiment 3, in contrast to Experiment 2. However, they are homogeneous landwards, similarly to Experiment 2, since the probability of flooding is near zero in this region.

Similarly to Experiment 2, we estimated land rent as a function of distance to the coast and the CBD and individual coefficient of perceived damage, using cubic regression ($R^2 = 0.8457$). The estimated 2D land-rent gradient, plotted in the dot-dashed line in Figure 5, falls seawards from the CBD compared to the dashed estimated rent gradient of Experiment 2. Although it is still above the reservation price beyond the safety contour, the total value of the property under risk is much lower. Thus, land near the coast is more valuable for buyers parameterized with the skewed rather than the uniform distribution.

Discussions and Conclusions

Micro-level data from surveys is being used more frequently as a building block for empirical agent-based models. In this paper, we analyzed the results of a survey carried out in the Dutch province of Zeeland that was designed to, among other things, elucidate individual risk perception and factors affecting location choice (Krywkow, Filatova, and van der Veen 2008). Consistent with other surveys, the survey showed that Dutch people generally have low or very low worry about coastal flooding affecting them personally. The survey also showed that proximity to work is the most important factor that affects individual choice of location, followed by environmental amenities, with safety from flooding receiving the lowest rating. We constructed our expected utility function to include these main location choice factors, and we used the distribution of worry from the survey to parameterize agents in the ALMA-C model.

We performed three experiments with our ABM of a coastal land market. First, homogeneous buyers were parameterized with the mean value of worry about flood risk, reflecting a representative agent approach. Results mirrored those that would be expected from an analytical Alonso style model of the same system. For this model parameterization, flood risk outweighs amenity value along the coast for the representative agent. This model parameterization leads to relatively lower values, and therefore less development, in the flood-prone zones. Regression analysis of model-generated data demonstrates that the land rent is positively correlated with distance to the

coast, as shown in the downward slope of the estimated rent gradient towards the coast (Figure 5). These model results are consistent with the survey results, which indicated that *on average* people are more likely to pay for safety than for amenities (Table 1) and that average WTP for safety is slightly higher than WTP for amenities (Table 2).

However, in the real world, it is not the average, representative buyer who is active in the land market, but rather a diverse distribution of buyers. Therefore, in our second experiment, heterogeneous buyers were parameterized with the leftward-skewed survey distribution of worry about flood risk. Compared to the homogeneous population, the land market outcome based on the real-world distribution of perceived flood damage showed a higher level of development in the flood prone zone, with a significant proportion of urban land value concentrated in this region. These results demonstrate the utility of the agent-based modeling approach, which facilitates estimation of a land-rent gradient based on market equilibrium land transaction prices produced by heterogeneous buyers operating over a spatially heterogeneous two-dimensional landscape.

Note that in this case the coast serves as a net attractor: the estimated rent gradient slopes upwards in the direction of the coast. In other words, given a realistic, skewed distribution of buyer risk perceptions, those with relatively low risk perceptions will express their relatively high WTP for coastal land through engaging in land market transactions in the risky zone, consistent with the WTP survey results. While these results showed that the majority of the respondents had a positive WTP for safety (66.51 percent) (Table 1), about 17 percent expressed a zero WTP for safety. Consistent with the survey data, modeled buyers with low "worry" have relatively high bids for land along the coast, and those with a higher level of "worry" have higher WTP for safety. Sorting between these agent types occurs through bilateral land market trading. Based on buyer's simulated WTP functions, the land market allocates people with a lower coefficient of perceived damage closer to the coast and buyers with high "worry" to the safer areas farther from the coast. Regression analysis of the model-generated data also shows that land value is negatively correlated with individual perceived damage (Table 5), as expected.

In our third set of experiments, heterogeneous buyers were parameterized with a uniform distribution of the coefficient of perceived damage, in order to show the difference between micro-level parameterization with skewed data (Experiment 2) vs. uniform data (Experiment 3). Driven by the existence of agents with relatively low levels of risk perceptions, more development and higher land values occurred in the risky zone than in the representative agent model, in spite of the fact that the mean level of risk perception in this model was higher than that in the representative agent model. However, consistent with the higher mean risk perception and form of the distribution of risk perceptions, which resulted in a lower proportion of agents in the low risk perception groups, less development occurred in the risky zones with the uniform distribution than with the real-world skewed distribution. This implies that even if decisions were made based on random guesses about flood risk in the coastal zone area, they would still result in fewer developments and less potential damage in the risky zone than what is happening when buyers in the land market have the skewed risk perception specific to the Dutch population.

From a modeling perspective, these results demonstrate the influence of buyer heterogeneity on land market outcomes—not simply the importance of acknowledging heterogeneity, but the importance of understanding the distribution of agent characteristics, possible in an empirical context only through high-quality micro data inputs. From a policy perspective, these results highlight a challenge faced by policymakers worldwide when individuals who underestimate risks settle in hazard-prone areas. As more land is converted into urban use and property at stake rises, the pressure on the government to fund structural defense measures (e.g., beach nourishment, dikes) to protect these individual investments grows. If government steps in and provides compensation for potential damage or offers publicly funded protection, this further unleashes development in hazard-prone but amenity-rich areas, at larger societal costs. While much is discussed about this self-reinforcing cycle in the United States (Wiener 1996, Barnhizer 2003, Kunreuther and Pauly 2006), this issue is largely neglected within the Dutch water management policy. The model presented in this paper helps visualize the effects of

low risk perception on spatial patterns and land rents in hazard-prone areas, and may help design policies that influence individual behavior to promote socially desired outcomes. Various instruments that help individuals integrate risks in their location decisions (e.g., risk communication, financial instruments, or engineering measures) may be employed to increase individual responsibility for living in hazard-prone areas (Filatova, Mulder, and van der Veen 2011). In the absence of such instruments and given the current structure of risk perceptions in the Netherlands, a significant degree of high-valued development is likely to occur in these risky zones, creating economic hardship and a major challenge for government if flood damage were to occur.

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