Risks and Hedonics in Empirical Agent-based land market (RHEA) model

Floods risks, housing markets and climate change: modelling behavioural responses in an artificial society

Koen de Koning and Tatiana Filatova

University of Twente, The Netherlands

Model description (ODD+D)[1]

1 Overview

1.1 Purpose

Risks and Hedonics in Empirical Agent-based land market (RHEA) model aims to provide a methodological platform to simulate the aggregated impact of households' residential location choice and dynamic risk perceptions in response to flooding on urban land markets. It integrates adaptive behaviour into the spatial landscape using behavioural theories and empirical data sources. The platform can be used to assess: how changes in households' preferences or risk perceptions capitalize in property values, how price dynamics in the housing market affect spatial demographics in hazard-prone urban areas, how structural non-marginal shifts in land markets emerge from the bottom up, and how economic land use systems react to climate change. RHEA allows direct modelling of interactions of many heterogeneous agents in a land market over a heterogeneous spatial landscape. As other ABMs of markets it helps to understand how aggregated patterns and economic indices result from many individual interactions of economic agents.

The model could be used by scientists to explore the impact of climate change and increased flood risk on urban resilience, and the effect of various behavioural assumptions on the choices that people make in response to flood risk. It can be used by policy-makers to explore the aggregated impact of climate adaptation policies aimed at minimizing flood damages and the social costs of flood risk.

[1] The ODD+D description of the original model of Filatova 2015 (in *Computers, Environment and Urban Systems; Volume 54, pp 397-413*) has been altered to match the current version of the RHEA model.

1.2 Entities, State Variables and Scales

The main agents in the model are households willing to buy and sell properties in a city where (local) flooding is a reoccurring phenomenon. They form preferences for residential property characteristics, and they may or may not take into account that some properties are at risk of regular flooding, depending on their risk perceptions. The environment consists of residential parcels that represent spatial goods. The agents are connected through the market.

State variables that are used in this base model are listed in Tables 1 - 2.

Table 1: State variables related to the spatial landscape of RHEA

Variable name	**Brief description**	**Value**
I. Spatial landscape (GIS parcel data)		
ID	A unique ID of a GIS parcel (spatial good)	***
Price	An attribute of a parcel where first seller's asking price and then market transaction price are recorded. Property prices are in 2004 dollars following the dataset of Bin et al (2008).	Endogenously determined
onSale	Indicates whether this parcel is for sale during in the current time step	TRUE/FALSE
Tradershere	Indicates the number of traders interested in the property	***
timeOnMarket	Counts the half years which this parcel is for sale on a market	Endogenously determined
FloodIns	Indicates the annual costs of flood insurance (in USD) on a property on the bases of regulations by the US Federal Emergency Management Agency (FEMA)	***
GIS location	X and Y coordinates of a parcel	***
Area	Surface area of the GIS parcel	Uploaded from GIS dataset and randomised to avoid multicollinearity
Bedrooms, BEDRMnorm	Number of bedrooms and the normalised value between 0 (lowest) and 1 (highest)	
Age, AGEnorm	Year house was built subtracted from 2004 and the normalised value between 0 (highest) and 1 (lowest)	
Sqft, ln(sqft), SQFTnorm	Total structure square footage, the log of square footage and the normalised value of the log between 0 (lowest) and 1 (highest)	

Acres, ln(acres), ACRESnorm	Total lot size measured in acres, the log of the lot size and the normalised value of the log between 0 (lowest) and 1 (highest)	
Neighbourhoud quality (residuals), RESIDnorm	Neighbourhood quality is represented by the residuals of hedonic regression on property transactions after controlling for age, square footage, acreage, number of bedrooms and probability of flooding. RESIDnorm is the normalised value of the residuals between 0 (lowest) and 1 (highest)	
pflood	Probability of flooding (0, 1:100, 1:500)	
Nghbrs.100FZ	Indicates whether there are any properties in the vicinity that are located in the 1:100 reoccurring flood zone	TRUE/FALSE
Nghbrs.500FZ	Indicates whether there are any properties in the vicinity that are located in the 1:500 reoccurring flood zone	TRUE/FALSE

Table 2: State variables related to household agents in the RHEA model

II. Households (traders) – parent class		
PID	For homeowners this is a unique ID that represents the house they occupy. For buyers it represents the unique ID of the property that they would like to buy	***
Utility	Dimensionless utility that the household receives from occupying a certain home. It can be used by buyers to identify which property they want to purchase.	Equation 2
House.pflood	The probability that the households' home will get flooded, based on the FEMA flood zone maps. For buyers this variable concerns the probability of flooding for the property that they are interested in buying	
MarketStatus	A market status of a household agent in a current time step	Buyer, seller, traded
Income	Household annual income (empirical distribution/average empirical). Source: USA statistics[2]	

[2] United States Census Bureau, http://www.census.gov/hhes/www/cpstables/032012/hhinc/toc.htm
Statista, http://www.statista.com/statistics/203247/shares-of-household-income-of-quintiles-in-the-us/, http://www.statista.com/statistics/203183/percentage-distribution-of-household-income-in-the-us/

Budget	Upper boundary of the budget that buyers have available for the housing good. This is dependent on the annual income of the household. Source: Quigley and Raphael 2004	
minBudget	Lower boundary of the budget that buyers consider spending on the housing good.	
Myprice	Stores the value of a bid or ask price agent is ready to pay for a certain parcel	Equations 3-5
Refused	Counts how many times an agent did not succeed in buying or selling a property	***
CORinsurance	Indicates whether the seller should adjust its ask price for the anticipated costs of flood insurance in case insurances are mandatory.	TRUE/FALSE
Exp.flood	Indicates whether the agent has experienced flooding in his town	TRUE/FALSE
Exp.damage	Indicates whether the agent has ever experienced damage to their property as a result of flooding	TRUE/FALSE
Learning.Not	Indicates whether the agent has a lack of information about flooding. This variable is TRUE, when all of the variables *Exp.flood, Learning.Not, Learning.NewsMedia* AND *Learning.Nghbrs* are FALSE	TRUE/FALSE
Learning.NewsMedia	Indicates whether the agent is informed about flooding through news media	TRUE/FALSE
Learning.Nghbrs	Indicates whether the agent is informed about flooding through experience of their neighbours	TRUE/FALSE
LikelyDamage	Indicates the agent's perceived likelihood that their house will get damaged by floods	Updated endogenously in the model. See section 2.3
Costs.FloodIns	Indicates the agent's perceived costs of flood insurance	
Effect.FloodIns	Indicates the agent's perceived effectiveness of flood insurance in minimising financial costs of flooding	
Costs.MovingOut	Indicates the agent's perceived costs of moving out of their home	

Effect.MovingOut	Indicates the agent’s perceived effectiveness of moving out of the flood zone as a strategy to minimise future risk of flooding	
Prob.FloodIns	Indicates the agent’s probability that they will get flood insurance on their home.	
FloodIns	Indicates whether the agent has flood insurance	
FEARscore	Indicates the agent’s fear towards flooding	
FloodIssue	Indicates whether a buyer takes flood zones into account in their search for a new home	
BEHAVscore	Score that changes dynamically on the bases of new information and that will affect the buyers’ tendency to avoid buying properties in the flood zones.	
AVOID100FZ	Indicates whether the buyer avoids the 1:100 year reoccurring flood zone in their search for a new home	
AVOID500FZ	Indicates whether the buyer avoids the 1:500 year reoccurring flood zone in their search for a new home	
LikeliMoveOut	Indicates a homeowners likelihood that they will put their house on sale in order to avoid the risk of future flooding	
Mortgage	Indicates whether homeowners have a mortgage on their home	TRUE/FALSE
Financed	Indicates what % of the purchase sum was financed by mortgage	0-100
yM	Indicates the years still left on the mortgage. By default it is assumed that every mortgage has a payback period of 30 years.	0-30
Debt	Indicates the amount of debt that homeowners still need to pay back on their mortgage	
SellerStatus	Variable that keeps track of sellers’ success on the market, as well as whether they just want to relocate (=attempting to sell) or they want to sell their home because of the risk of natural hazards (=evading hazard)	“traded”, “cannot afford selling”, “none”, “inactive”, “failed to sell”, “attempting to

		sell", "evading hazard"
AGEnorm	Buyers' preferences for new properties versus old properties. A positive value means they prefer new properties. The larger the absolute value, the larger the relative importance of this attribute compared to other attributes.	Can be positive and negative ranging from -99.2 to +100. Combined they sum up to 100 Equation 2, section 2.2
SQFTnorm	Buyers' preferences for surface area. A positive value means they prefer larger houses over smaller houses. The larger the absolute value, the larger the relative importance of this attribute compared to other attributes.	
ACRESnorm	Buyers' preferences for lot size. A positive value means they prefer larger lots over smaller lots. The larger the absolute value, the larger the relative importance of this attribute compared to other attributes.	
BEDRMnorm	Buyers' preferences for number of bedrooms. A positive value means they prefer more bedrooms. The larger the absolute value, the larger the relative importance of this attribute compared to other attributes.	
RESIDnorm	Buyers' preferences for neighbourhood quality. This value is always positive. The larger the absolute value, the larger the relative importance of this attribute compared to other attributes.	
II.1 Buyer – subclass of traders class		
A-delta (D_{neg})	Difference between bid and ask price, which buyer is ready to accept in price negotiations; equals to her half yearly rent	Endogenously determined
Bid price	Buyer's bid price for a specific spatial good	Section 2.2
II.2 Seller – subclass of traders class		
A-delta (D_{neg})	Difference between bid and ask prices, which seller is ready to accept in price negotiations; equals to his half yearly rent and grows with timeOnMarket	Equation 1
Ask price	Asking price the seller assigns to the cell he owns	Sections 2.2.-2.3

The model is spatially explicit: at initialization GIS data (Bin et al. 2008; Bin and Landry 2013) are uploaded to generate the empirical landscape. To account for the extent of flooding, the model has to two GIS datasets that represent different case studies in North Carolina, USA: Beaufort and Greenville. Both cities are in an area where hurricanes caused major flood damage to properties. They differ in the extent of the flood zone – Beaufort has a larger share of hazard-prone properties, and hence the impact of flooding is more widespread. One time step in RHEA is equal to half a year.

1.3 Process overview and scheduling

The main processes in the ABM are trading of residential properties and the dynamics of risk perceptions in response to flooding events. Each time step the trade process consists of several phases: listing of vacant spatial goods in a market by sellers, search for the best location under budget constraint and risk-avoidance strategies by buyers, formation and submission of bids by buyers to sellers, evaluation of received bids by sellers, price negotiation, transaction and registration of trade, and finally updating of market expectations by realtors. The sequence of events in one time step is presented in Figure 1. RHEA borrows the base trade flow logic of the ALMA model (Filatova et al. 2009a; Filatova et al. 2011) and extends it with a different procedure to initialize sellers (box I, Figure 1), accounts for empirical landscape and hedonic price function (box II and III), with new price negotiation (box IX) and adaptive price expectations (box XII and XIII).

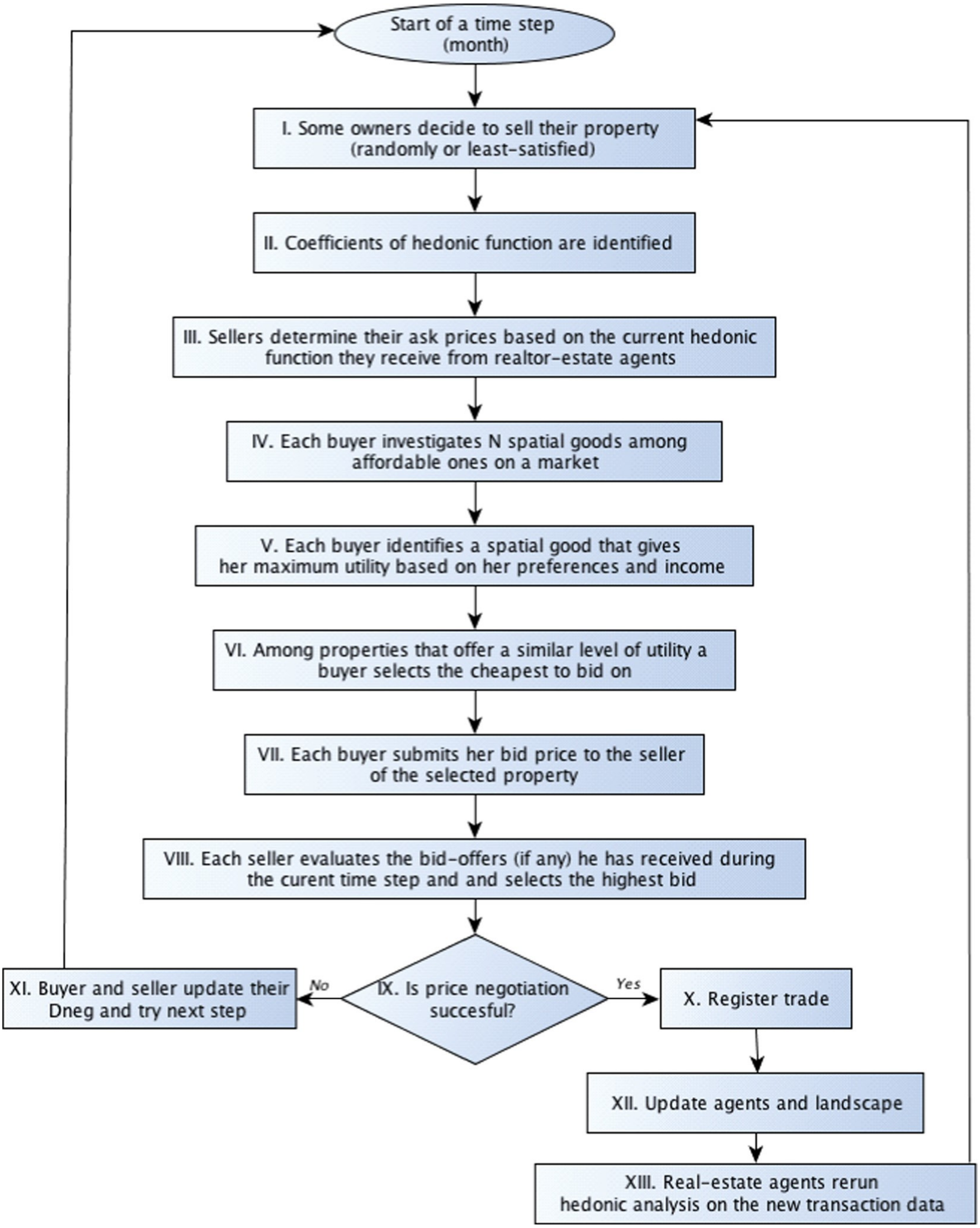

Figure 1. Dynamics of the trade process: a sequence of actions, which agents perform within 1 time step of the bilateral agent-based housing market with expectations formation. *Source: Filatova 2015*

2 Design concepts

2.1 Theoretical and empirical background

The RHEA model uses microeconomic demand, supply, and bidding foundations of spatial economics. However, we extend the traditional economic utility maximisation problem by accounting for behavioural heuristics. In particular, psychology theories such as protection motivation theory and the affect heuristic theory contribute to guiding the behavioural rules of agents. Our ABM uses a number of empirical datasets for calibration and validation:

(1) two GIS datasets of actual properties (Bin et al. 2008; Bin and Landry 2013), along with information on structural characteristics and flood zone location based on federal flood maps (FEMA 2018[3]),
(2) time series of housing sales before and after a flood over 17 years (Bin and Landry 2013),
(3) 2 x 2 hour in-depth interviews with real estate agents to specify the main architecture of the market (how ask and bid prices are formed, how agents negotiate prices, how they adjust prices, how learning on price expectations is happening) and 19 x half-hour to one hour interviews with real estate agents on how flood zones affect the decisions of buyers and sellers in the market,
(4) surveys among 519 buyers and 521 sellers, of which some were affected by the floods caused by hurricane Harvey in 2017 (de Koning et al. 2019 – manuscript under review).

2.2 Individual Decision-Making

There are two main trading agents in the model (buyers and sellers) that interact in the market, and one central realtor agent that informs buyers on an efficient ask price.

<u>Realtor behaviour</u>: At the beginning of a trading period active sellers announce their **ask prices**. This is done by combining hedonic regression on housing transactions with spatial interpolation (kriging) of the residuals of the regression. Following de Koning et al. (2016), hedonic regression is run with only a few of the main housing attributes: square footage, acreage, age, number of bedrooms and flood zone location. The residuals of the regression represent most of the location-specific attributes associated with the market value of a property, which is then interpolated over space using kriging. At the initialization stage this hedonic function, coefficients and residuals for the kriging part come from Bin and Landry (2013). As model runs and new transactions occur the hedonic analysis and kriging are re-run on simulated transactions. Regression coefficients may change as for example risk perceptions are evolving or new households with different preferences for locations are arriving to the city. On top of hedonic analysis and kriging, the algorithm that forms sellers' ask price takes into account the demand for a segment of a market in the previous time step. For each property, the realtor checks the demand for a group of properties with the same characteristics. The observed demand for these properties relative to the expected demand (at time t-1) determines if the price should be lowered or raised (at time t). The maximum amount by which the price is changed is captured by a variable called 'alpha', which can be adjusted by the user. Alpha is set at 10% by default. This variable plays a large role in the simulations when flood risk perceptions and experience enters the decision making of buyers. When a large number

[3] FEMA Flood Map Service Center, https://msc.fema.gov/portal/home

of buyers avoid properties in the flood zone, the price of properties in the flood zone must be lowered to attract more buyers.

Sellers' behaviour: at model initialization each property has an owner and some of those may decide to put it for sale, i.e. become sellers (box I, Figure 1). The choice of property owners who are to become sellers occurs in two stages in RHEA. First, every year the fraction of properties for sale and its standard deviation is defined exogenously. The actual annual number of houses going for sale is a random number generated from the normal distribution based on these two. In the future versions of the model this number could be made endogenous. Secondly, households that reside within a flood zone may choose to put their house on sale and look for a home in a safer location, which according to our survey data is more likely to happen when they have experienced a flood. As the simulation goes on, settled households may decide to relocate.

After buyers make their choices (boxes IV-VII, Figure 1), all sellers check how many bid-offers they received. They choose the highest bid to engage in price negotiations (box VIII, Figure 1)). The **transaction price** is defined through a price negotiation procedure, which is based on bid and ask prices and relative market power of traders (see section 2.6).

Seller's price formation (section 2.3) and choices in price negotiation depend on the past events and experiences, thus they adapt to changing endogenous variables. Specifically, sellers have a memory where they record a number of consequent unsuccessful trade attempts (N_{USTr}). Each seller has a threshold value (D_{neg}), which he compares to the difference between his ask price and the highest submitted bid price for his property during price negotiation procedure (section 2.6). At the start of a seller's trading history, his D_{neg} is equal to one half year of his mortgage estimated based on the price at which he bought the house (H_{tran}). As his N_{USTr} grows, the seller adapts his threshold value D_{neg} for one extra half year of rent, i.e.:

$$D_{neg} = kH \times H_{tran} \div 12 \times (1 + N_{USTr}) \quad (1)$$

Here kH is a coefficient to translate the property price (H_{tran}) into an annual payment.

Buyers' behaviour: Each time step a number of new buyers enter the market, approximately equivalent to the number of new properties on sale to avoid creating an excess of demand or supply artificially. Buyers randomly choose five properties affordable for their housing budget which varies across households. Insurance influences buyers' decisions first in this phase. In the model with 100% insurance uptake, buyers limit their budget for properties in the flood zone to reserve fund for insurance costs. Next, buyers choose one among five affordable properties that gives them the highest utility. Their utility for owning a property depends on a bundle of property attributes, neighborhood quality and a potential exposure to flood hazard. The base multi-attribute utility function (U_{0L}, Eq.4.1) for a house in a safe area is parameterized using weights (A_i) that reflect relative importance of each characteristic ($X_{i,norm}$):

$$U_{0L} = A_i * X_{i,norm} \quad (2)$$

The weights (A_{ij}), which indirectly measure preferences of an agent *j* for a particular attribute *i*, are based on de Koning, Filatova, and Bin (2017) which examines HA of actual sales using only the key housing characteristics[4] that drive the variation in sales prices[5]. Table 3 presents the ANOVA results illustrating the fraction of variance explained by each input variable, including the residual variance, which captures neighborhood quality. The relative importance of each input variable in the variation of property prices in Table 3 serves as a benchmark for the buyers' preferences. The sum of all A_{ij} equals to 100 for every agent *j*. The property attributes (X_i) are normalized between 0 and 1 depending on the sign of the hedonic regression coefficients[6].

Table 3. Relative importance of property attributes in the agents' utility function

Input variable (X_i)	Mean weight (A_{ij})	Min weight (A_{ij})	Max weight (A_{ij})
Age	18.2	-99.2	100
ln(Square footage)	35.2	-19.9	100
ln(Acreage)	4.4	-49.9	100
Number of bedrooms	6.4	-49.9	100
Neighbourhood quality	35.8	0.10	95

Buyers have subjective perceptions of risk, which are dynamic over time. Their risk perception variables determine whether buyers avoid buying properties in the 1:100 and 1:500 year reoccurring flood zones. This affects the demand for risk-prone properties. More on how sellers and buyers alter their risk perceptions is explained in section 2.3.

After a buyer has found the property that gives her the maximum utility, she submits her **bid price** to a seller (box VII, Figure 2). Buyers bid differently depending on how long a property is on a market and on their relative market power (Equations 6-7). Real-estate guidelines suggest that buyers bid between 3-5% below ask price, and up to 7-10% below ask price if they want to be aggressive and if a property is on the market for a long time:

$$H_{bid} \in [(H_{ask} - h); H_{ask}] \tag{3}$$

where h is a random number between 0-10% of the ask price of a seller.

[4] We used data from Bin and Landry (2013) that includes 9,793 residential property sales between 1992 and 2002.

[5] Note that we do not include the dummy variable that describes whether or not a property is located in a flood zone here as it enters the analysis later.

[6] For a positive regression coefficient the maximum gets assigned the value 1 and the minimum gets assigned the value 0. It is vice versa for negative coefficients.

If it is a sellers' market – that is, there is excess demand for certain areas – then buyers need to be more strategic and bid high enough to assure they actually get the property that maximizes their utility.

$$H_{bid} \in [H_{ask}; (H_{ask} + h)] \quad (4)$$

However, in any case buyer's bid price should not exceed her **reservation price,** which means that her annual payment should not exceed 30% of her annual income (Heckbert and Smajgl 2005).

2.3 Learning

One of the core decisions in decentralized ACE markets is the learning process regarding prices (LeBaron 2006; Tesfatsion 2006).

Real-estate agent and formation of price expectations: RHEA builds on previous research on agent-based LMMs and introduces an price expectation algorithm based on successful as well as unsuccessful transactions. Implementation of adaptive price expectations is realized in two stages: (1) trace housing price changes accounting for spatial goods heterogeneity, and (2) capture market dynamics. The assumptions on the process of real-estate agent price formation and negotiations between buyers and sellers were validated with 19 semi-structured interviews with real estate agents of 30-60 minutes.

To model the first stage of price expectation RHEA relies on basics of empirical research in urban and regional economics. In particular, according to Hedonic Price Modeling a house is a bundle of quantitative and qualitative characteristics (Rosen 1974). Thus, a price of a residential parcel can be expressed as a function of those attributes – presented as 5 GIS attributes and the interpolated residuals (through kriging) that represent neighbourhood quality. Marginal implicit prices can be interpreted as marginal willingness to pay of a representative household for specific housing attributes. This application of RHEA adopts the hedonic function estimated for the area based on the GIS data used to initialize the landscape (Bin et al. 2008):

$$\ln H_{tran} = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \varepsilon \quad (5)$$

Here $\ln H_{tran}$ is the log of transaction price, x_i is a variable for the i^{th} housing attribute (structural), β are regression coefficients, and ε is the error term that captures the value of the (unspecified) spatial attributes used for spatial interpolation.

At initialization realtors are endowed with coefficients of the original hedonic analysis of Bin and Landry (2013). At the end of each time step, all successful transactions get registered in a file (Trade results.csv) together with all the attributes of traded agents and properties. Each half year a real-estate agent checks if there are enough transactions to run a comparable sales analysis. If yes, then he runs a hedonic analysis on the new transactions from the last trading period (6 months). It is also possible to switch off this stage of adaptive price expectation by setting up R-hedonics on ‘Static’. In this case the hedonic model based on empirical analysis (Bin and Landry 2013) will be used throughout the whole simulation.

Updating risk perceptions: RHEA model agents update their attitudes towards flood risk on the bases of the information they have available during the simulations. This will be affected by the occurrence of floods, media coverage about floods and exchange of information among people in a neighbourhood. This is informed by empirical data (survey data) about how flood hazard risks and experience with floods affect people’s choices where to live in relation to the flood zone (de Koning et al. 2019 – under review). We ran Bayesian statistics and regression analysis on survey results, upon which we built the module of flood risk and behavioural choices of buyers (Fig. 2) and sellers (Fig. 3). We used the output of the analysis directly in the model to set the Bayesian learning rules in which agents update their risk perception variables and their behavioural responses correspondingly. The risk perception variables and behavioural responses depend on the individual experience with flooding in town, on the damage to own property and on the damage to neighbouring properties. In the risk context people exhibit bounded rationality. In particular, homeowners in the flood zone weight their perceived probability and perceived damage while making decisions under risk (i.e. behave according to protection motivation theory) before they experience any flooding. As soon as they have personal experience going through this shock, more psychological reasoning kicks in: for example with fear dominating the decisions to move away from the flood zone (Fig. 3). Every half year homeowners’ update their perceived likelihood of damage and likelihood to abandon their risk-prone property. Also, the fear score of all households and buyer's tendency to avoid the flood zone get updated according to their information sources (Fig. 2 and Fig. 3).

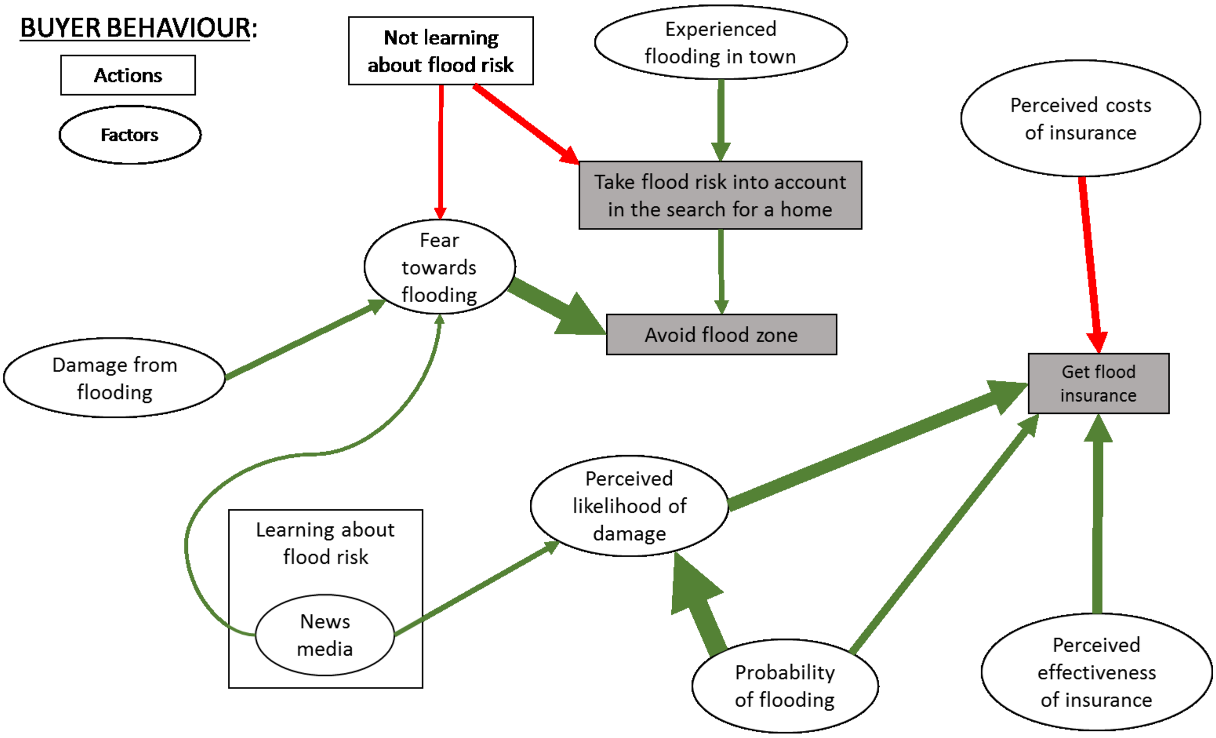

Figure 2. Schematic representation of buyer behaviour in response to flood risk. Red indicates negative effects and green the positive. The strength of the impact is given by the thickness of the lines. The main responses of buyer agents in the model are highlighted in grey. Source: *de Koning et al (Under review)*

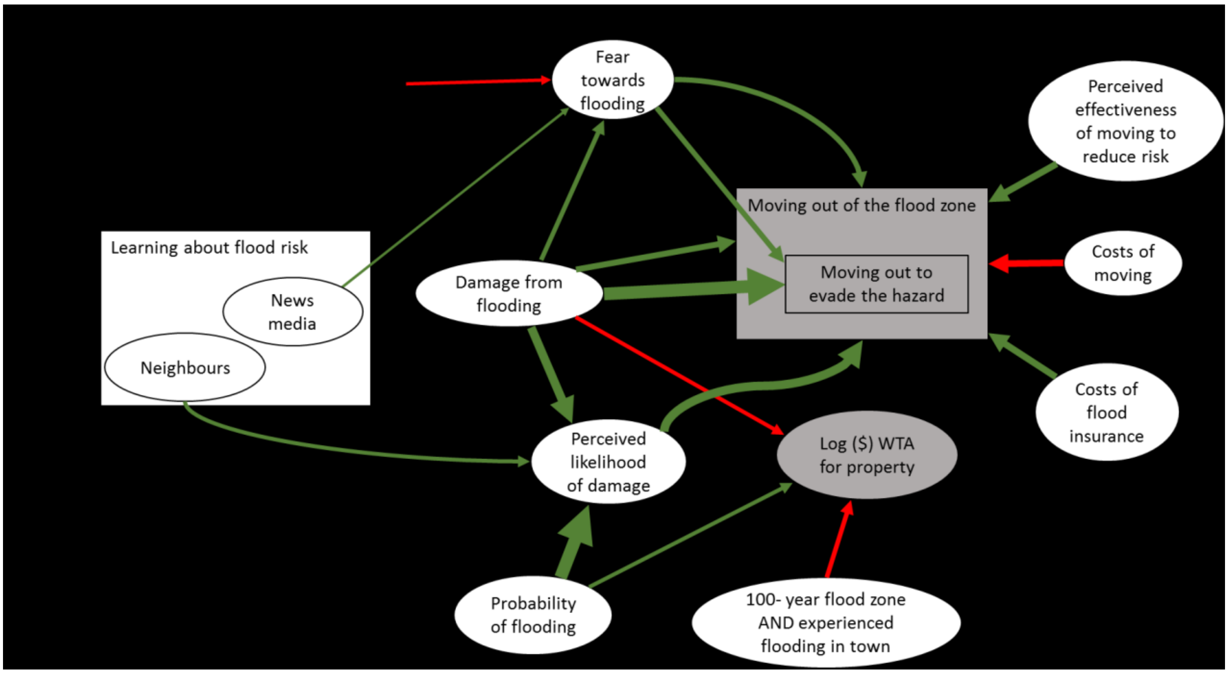

Figure 3. Schematic representation of seller behaviour in response to flood risk. Red indicates negative effects and green the positive. The strength of the impact is given by the thickness of the lines. The main responses of seller agents in the model are highlighted in grey. The box 'moving out of the flood zone' indicates household agents that sell their property for all sorts of reasons, and choose to live outside the flood zone after the move. The box 'moving out to evade the hazard' is a subset of the former group highlighting agents sell their house explicitly to escape the hazard of flooding. Source: *de Koning et al (Under review)*

2.4 Individual sensing

Information about estimates of a property values is public. However, buyers are assumed to be boundedly-rational. Bounded rationality captures the fact that an individual is not able to foresee all the consequences of his choice, take into account all the factors, and has limited computing abilities (Simon 1997). Searching for a house in reality is very costly (time-wise and money-wise). Not all properties are listed in online databases, choice and viewing of listed properties is time-consuming. Since a global optimum is not likely to be identified in real-world housing markets, buyers do not search for the maximum throughout the whole landscape, but rather find a local maximum among a set of randomly chosen parcels. Sellers' ask prices are public information but a buyer is not aware of the bids other buyers make.

With regard to floods, homeowners have information about whether any properties within a user-specified radius (*NeighbourR*) have been flooded.

2.5 Individual Prediction

Traders rely on pricing information, which is provided by the price prediction algorithm.

2.6 Interaction

Agents are involved in market interactions with each other: (a) buyers and sellers engage in direct interactions during negotiations, (b) residential property prices are emergent outcomes of direct buyers and sellers interactions; (c) buyers compete with each other submitting bids to the same seller; (d) sellers update their threshold for accepting the difference between bid and ask prices (D_{neg}) if they were not successful during 1 trade period; (e) sellers adjust lower their price when demand reduces for properties in the flood zone. The outcomes of these interactions also indirectly affect future trades through real-estate agents updating their price expectations (section 2.3).

The social interaction happens when neighbours communicate about flood risk. Homeowners observe whether their neighbours have been affected by a flood (Figure 3, section 2.3). This will affect their perceived likelihood that their property could be affected by floods as well.

During the trade process (box IX. Figure 1): If a seller has at least one bid submitted he engages in price negotiations with the buyer who offered the highest bid price. Naturally, if her bid price is higher than seller's ask price, then the trade is successful and final transaction price is equal to this bid (box (1), Figure 4). If the highest bid is below the original ask price, then the market power of agents plays a role (box (2) Figure 4). Specifically, if the seller has more than 1 bid offered, then the highest-bid buyer is the first one to reconsider his bid price. The highest-bid buyer checks if the opportunity costs of waiting another half year for another trade attempt (her D_{neg}) are comparable to the difference between the bid and ask prices (box (3) Figure 4). Here D_{neg} of a buyer is operationalized as one half year of renting an average house in the city[7], which is updated with time as residential housing prices change. If it is beneficial for the buyer to accept the ask price instead of waiting another half year for a trade attempt, then she accepts the ask price and trade is successfully registered. However, if the seller receives only one offer-bid, then he is the one to reconsider his ask price (box (4) Figure 4). In particular, he compares the difference between bid and ask prices to the opportunity costs of waiting another half year (his D_{neg}) and accepts the bid price, if comparison is in its favor. The D_{neg} of a seller is operationalized as one half year of mortgage for his property at the start of sellers trading history and gets updated with every unsuccessful trade attempt (section 2.2). If the seller and the buyer do not agree on a price the negotiation fails. Potentially one may consider advancing the negotiation procedure at the stage of box (4), Figure 4, by making sellers estimate their probability of selling in a given time at a given price and have this probability updated as in (Ettema 2011).

[7] RHEA does not model a residential renting market explicitly. Thus, the average rent in the city is equal to average mortgage payment in this city and is the same for all buyers. In case a rental market is modeled explicitly in parallel to the ownership market, the half yearly rent would be heterogeneous across households.

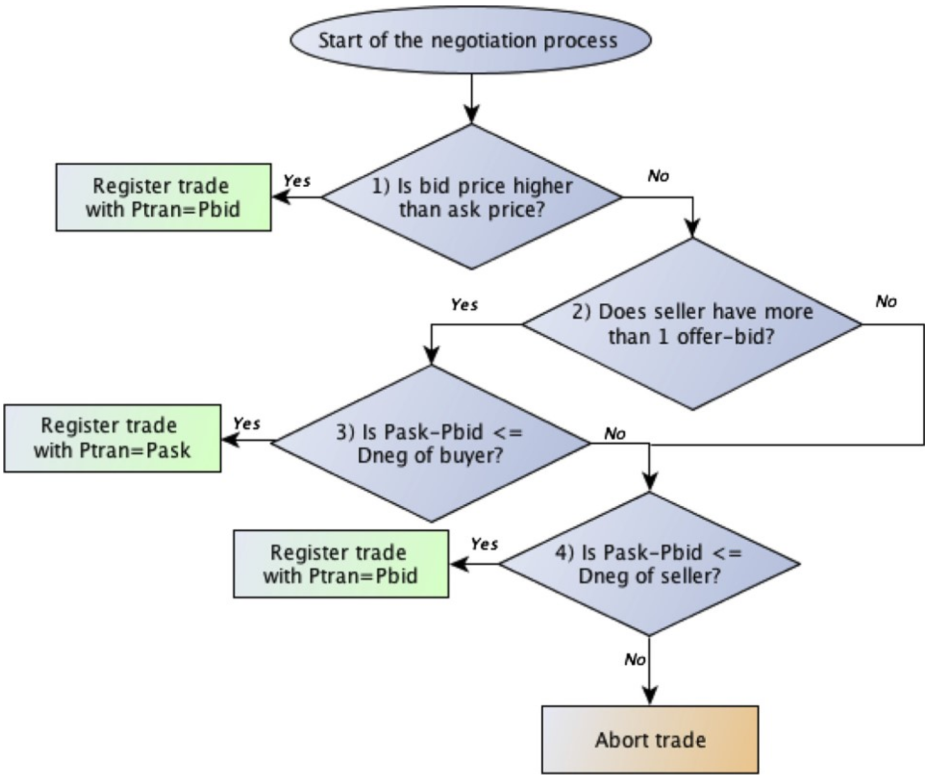

Figure 4. The simulation flow of the price negotiation process (Section 2.2.6). Here: buyers' opportunity costs of waiting another half year for another trade attempt (Dneg of a buyer) are equal to 1 period of rent, seller's opportunity costs of waiting another half year (Dneg of a seller) are equal to 1 period of mortgage. Both of them are updated following unsuccessful trades.

The overall trade process may result in the following outcomes, coded with 'trade codes' (Table 4).

Table 4: Possible outcomes of the trade process

Trade code	**Meaning**
TC1	Trade attempt is successful when Bid>Ask;
TC2	Trade attempt is successful when Bid<Ask, seller has more than 1 offer-bid, and buyer raises her bid;
TC3	Trade attempt is successful when Bid<Ask, seller has more than 1 offer-bid, and seller lowers his ask to match the highest bid;
TC4	Trade does not occur because Bid<Ask and traders did not agree;
TC5	Trade attempt is successful when Bid<Ask, seller has only 1 offer-bid, and he lowers his ask;
TC6	Traders did not agree since for both it is cheaper to wait another half year;
TC7	Trade does not occur because there were no bids offered to a seller.

2.7 Collectives

Agents do not form any networks or other collectives.

2.8 Heterogeneity

Traders are heterogeneous in their preferences for specific housing attributes, their risk perception variables (Fig. 2 and Fig.3, section 2.3), their budgets, income, and their mortgage loans. More on budgets, incomes and mortgage can be found under 3.2.

2.9 Stochasticity

When the population of agents is created during initialization and consequent steps (for incoming buyers), all attributes (incomes, budgets, risk perceptions, preferences) are assigned randomly to agents. Moreover, during the model run the stochasticity comes in when property owners decide to become sellers, when buyers set up their bid prices, and when the number of incoming households is determined every step.

2.10 Observation

The model is operated in RStudio, which is less suitable for visualisation of the model dynamics during the simulations than NetLogo. Therefore, the model writes output files on all successful trades and trade attempts that can later be analysed with R or any other statistical software. The output is stored in a folder that can be specified by the user. By default the folder is called ‘Output’, which should be located in the folder that stores the model’s R code.

3 Details

3.1 Implementation Details

The model is implemented in RStudio using the packages “sp”, “rgdal”, “maptools”, “rgeos”, “GISTools”, “plotrix”, “foreign” and “gstat”. The model’s R code and associated input data is accessible via *comses.net*

3.2 Initialization and Scenarios

The model is initialized with either one of two case studies of actual property markets in North Carolina, based on GIS data of actual properties and their characteristics, Greenville (N=9793) and Beaufort (N=3481). The two cities differ in the fraction of properties that are located in the hazard zones: Greenville has 6.4% of the properties in the 100-year flood zone, and Beaufort has 29.9% of the properties in the 100-year flood zone and another 21.5% of the properties in the 500-year flood zone.

The number of sellers and buyers is user-defined. The properties going for sale at initialization vary across model runs.

The budget that buyers are ready to spend on housing is based on how much they earn. The agents (homeowners, buyers and sellers) have various levels of income based on U.S. national income data (Statista, 2017). When households enter the market as a buyer they allocate a certain budget to housing, which is a function of their income (Eq. 6). Each buyer spends a random percentage of its budget on housing, but low income buyers spend relatively more of their income on housing than high income households. The percentages of income that households allocate to housing is validated with survey data and U.S. national statistics (Statista, 2017).

$$e^{4.96+0.63*\ln(income)} \tag{6}$$

Furthermore, the housing budget does not exceed 30% of a households' income, which is a financial rule-of-thumb for homeowners and is often the mortgage limit supplied by mortgage lenders. In the model, the housing budget includes mortgage and flood insurance. The percentage of the housing transaction that is financed by mortgage, if anything, is also a random percentage drawn from a distribution based on survey data and U.S. national statistics (Statista, 2017). Some buyers are cash buyers and do not have a mortgage. Homeowners that do have a mortgage will pay off their mortgage linearly in 30 years. This is another important aspect of the model, because it determines whether homeowners are capable of selling their house. If the expected price of their property on the market has dropped below their mortgage debt, for example as a result of a major flooding event, they will abolish their trade attempt. These traders are identified as 'stuck' in their homes.

The user can specify 5 scenarios at initialisation: "Control", "Flood", "Extreme Flood", "Media", and "Flood and Media". These scenarios can be used to assess the impact of floods and media reports about floods on people's risk behaviour. The "Control" scenario is one without floods. The "Flood" scenario is one with a single major flood at time step T=102 (the first 100 time steps are needed for stabilising the market dynamics in the model). The "Extreme Flood" scenario is one with two major floods shortly after each other: at T=102 and at T=110. The "Media" scenario is one with annual reports about floods in the media after T=100. All households living in the 100 and 500 year reoccurring flood zones experience damage to their homes by the floods. All households in town (homeowners and buyers) update their experience with flooding – a binary true/false variable – after the floods. Housing prices reduce in anticipation of a drop in demand for properties in the flood zones. To capture this in the model, the flood affected sellers reduce their price by 13.8%, and sellers in the 100 year flood zone reduce their price by an additional 15.7% (empirically observed in the survey among sellers).

The 5 scenarios are run with the same random seed, and thus the output (sales and trade attempts) will only start to diverge at the moment when the scenarios start to diverge. Every iteration of a scenario will be run with a new random seed. The model keeps track of all the model runs that are written with a particular random seed, so that each simulation will result in unique output.

3.3 Input Data

Input files needed to operate the model are:

'incomes.txt' – a text file with fictional incomes based on US national statistics

‘Greenville.shp’, ‘Greenville.dbf’, ‘Greenville.shx’ – a GIS shapefile that highlights the boundaries (polygons) of the study area of Greenville.

‘Greenville_Random3.shp’, ‘Greenville_Random3.dbf’, ‘Greenville_Random3.shx’ – a GIS shapefile with the coordinates (points) and attributes of the parcels of Greenville.

‘Beaufort.shp’, ‘Beaufort.dbf’, ‘Beaufort.shx’ – a GIS shapefile that highlights the boundaries (polygons) of the study area of Beaufort.

‘Beaufort Random.shp’, ‘Beaufort Random.dbf’, ‘Beaufort Random.shx’ – a GIS shapefile with the coordinates (points) and attributes of the parcels of Beaufort.

‘Buyer preferences.csv’ – a table stat stores a list of fictional preferences for certain housing characteristics (Table 3). The preferences of each new buyer are drawn as a random sample from this table.

‘SimTimeEst.csv’ – a table that stores the coefficients that will estimate the approximate runtime of the simulations based on the specified number of time steps and case study.

‘SurveyDATA.csv’ – a table with all the relevant survey data used for initialisation of the agents in the model and for Bayesian updating of flood risk perceptions and flood-related behaviour of the agents.

3.4 Submodels

There are currently no submodels in the RHEA model