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Empirical agent-based land market: Integrating adaptive economic behavior in urban land-use models

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ABSTRACT

This paper introduces an economic agent-based model of an urban housing market. The RHEA (Risks and Hedonics in Empirical Agent-based land market) model captures natural hazard risks and environmental amenities through hedonic analysis, facilitating empirical agent-based land market modeling. RHEA is well grounded in economic theory and uses rich spatial data and econometric analysis. It moves beyond the existing work by explicitly simulating the emergence of property prices and their spatial distribution under adaptive price expectations of heterogeneous agents, advancing toward empirical modeling of agent-based land markets. At the same time RHEA operates in a realistic GIS landscape where realtor and households agents form ask and bid prices using empirical hedonic price functions. The simulation results demonstrate that this combination of theoretically sound micro-foundations in agents' behavior and empirical data is feasible. This opens opportunities to explore various methodological and policy-relevant research questions including exploration of abrupt non-marginal changes in markets and regime shifts in coupled socio-environmental systems.

1. Introduction

Spatial patterns of land values in real estate markets emerge from complex interactions of market dynamics, heterogeneous trader preferences, and heterogeneous attributes of the property stock. Various modeling approaches aim to represent the feedbacks between micro-foundations of actors' behavior and macro dynamics of property markets measured in land prices and their spatial patterns. There is a long tradition of modeling these spatial processes from the bottom up using statistics (Geoghegan, Wainger, & Bockstael, 1997; Irwin & Bockstael, 2002; Plantinga & Lewis, 2014; Sheppard, 1999), cellular automata (van Delden, Luja, & Engelen, 2007; Verburg, de Koning, Kok, Veldkamp, & Bouma, 1999), micro-simulation (Ettema, Arentze, & Timmermans, 2011; Miller, Hunt, Abraham, & Salvini, 2004) or agent-based methods (Brown & Robinson, 2006; Parker, Berger, & Manson, 2002). It is essential that computational models are based on micro-foundations, which are not only theoretically sound but are also empirically justifiable, especially if effectiveness of policy interventions is to be assessed.

This paper presents an innovative agent-based model (ABM) of a spatially explicit empirical housing market – RHEA (*Risks* and *Hedonics* in *Empirical Agent*-based land market model) – and explores its behavior under various micro-foundations.[1] Several recent papers provide comprehensive reviews of ABM methodology applied to socio-economic processes in space (An, 2012; Filatova, Verburg, Parker, & Stannard, 2013; Heckbert, Baynes, & Reeson, 2010; Matthews, Gilbert, Roach, Polhill, & Gotts, 2007; Schreinemachers & Berger, 2011) and review the state-of-the art in agent-based land market models (LMMs) (Ettema, 2011; Huang, Parker, Filatova, & Sun, 2013; Magliocca, Safirova, McConnell, & Walls, 2011; Parker & Filatova, 2008). Spatial ABMs applied on an urban scale generally either tend to use a comprehensive empirical landscape setting and some data to lay foundations for agents' behavior omitting theoretical assumptions about economic processes (Benenson, 1998; Brown, 2006; Dawson, Peppe, & Wang, 2011; Yin & Muller, 2007), or use a stylized landscape and little empirical micro-foundations of agents' behavior with theoretically-elegant

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[1] By micro-foundations this paper means the basic principles that lay out the foundations of individual agents' behavior. These include a specific theoretical basis as well as empirical information that is used to parameterize and/or validate these behaviors. The ability to generate market level phenomena and patterns based on detailed empirical data and theoretically-sound micro behavior provides a novel advancement in ABM.

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economic solutions (Ettema, 2011; Filatova, van der Veen, & Parker, 2009; Magliocca et al., 2011). There is a gap in the field: the feasibility of combining empirics and theory when designing micro-foundations of agents' behavior in spatial markets is underexplored.

ABMs are particularly strong in integrating socio-economic and environmental modeling, often within a spatial landscape, across scales, as well as exploring various market phenomena by going beyond stylized assumptions of equilibrium economic models. Yet, ABMs are often weak in connecting to empirical data when parameterizing various attributes and validating decision-making processes of agents (Boero & Squazzoni, 2005; Poggio, Lo, LeBaron, & Chan, 1999). In fact validation and parameterization is one of the main research challenges in the field of ABM (Filatova et al., 2013; Heckbert, Baynes et al., 2010; Heckbert & Bishop, 2011; Robinson et al., 2007; Smajgl, Brown, Valbuena, & Huigen, 2011; Windrum, Fagiolo, & Moneta, 2007). The benefits of connecting ABMs to empirical data are obvious. Firstly, while purely theoretical ABMs have an important added value (Boero & Squazzoni, 2005), their application for policy analysis is contingent on the use of empirical data for parameterization and validation. A consistent use of empirical data increases trust of various stakeholders in any model, including ABMs (Janssen & Ostrom, 2006). Secondly, ABMs are extremely flexible on the choice of behavioral rules at individual agent level and on the structure and frequency of interactions. This forces a modeler to face a choice of numerous variability in a model instantiation (Polhill et al., 2014). The parameterization of an ABM with the actual data filters the nearly-unlimited collection of options for micro-foundations or parameter settings to an easier-to-handle parameter set that produces an ABM world resembling a realistic case. Thirdly, data on individual choices over time and on the structure of human interactions permits an examination of the theoretical consequences of more realistic assumptions (Janssen & Ostrom, 2006). Empirical data could be used to design and parameterize realistic micro-foundations of an ABM or to validate macro outcomes of a simulation but preferably both (Boero & Squazzoni, 2005). Empirical methods for building ABMs such as surveys, stylized facts, archival and census data, participatory modeling, expert knowledge elicitation, participant observation, field and laboratory experiments, and GIS data have been extensively reviewed (Boero & Squazzoni, 2005; Heckbert, Baynes et al., 2010; Janssen & Ostrom, 2006; Robinson et al., 2007; Smajgl et al., 2011).

Advantages of using empirical data for an ABM are vast. However, there are also challenges, which may include: (1) maintaining a link between empirical data and a theory, assumptions of which an ABM is supposed to relax, (2) scaling up observed behavioral data to large population of artificial agents, (3) capturing behavioral change through time when empirical data often provides only a snapshot, (4) a necessity to collect case-specific data to match the design of an ABM, (5) difficulty in replication and generalization of the results since some methods of collecting data that is suitable for ABMs are difficult to reproduce, (6) translation of qualitative data into formal rules when coding (Heckbert, Adamowicz, Boxall, & Hanneman, 2010; Janssen & Ostrom, 2006; Robinson et al., 2007; Smajgl et al., 2011; Valbuena, Verburg, & Bregt, 2008; Windrum et al., 2007).

An empirical ABM of an urban economic system, which is well grounded in economic theory and could use readily available spatial data and economic empirical analysis, is not available yet. The RHEA model aims to address this gap. Specifically, theoretical micro-foundations of residential household agents' behavior are framed within urban economics theory (Alonso, 1964; Frame, 1998; Wu, 2001) and use adaptive price expectations. At the same time RHEA operates in a realistic GIS landscape where realtor and households agents form ask and bid prices using empirical hedonic price functions, i.e. empirically-estimated willingness-to-pay functions based on detailed spatial attributes of the property stock. Moreover, empirical micro-foundations include real income distributions, and behavioral rules of traders in a housing market validated through an interview with a US realtor.[2] The interview shed light on the fact (i) that sellers set prices based on realtors predictions, (ii) that buyers anchor their bids on seller's ask prices, (iii) that an outcome of price negotiations depend on market power of traders and their opportunity costs, and (iv) that prices, at which realtors anticipate to sell a house, depend not only on spatial and structural attributes of a house but also change dynamically with market conditions. In addition, some quantitative parameters of the models, such as percent of differences between bid and ask prices, and a period of recent sales realtors take into account when forming prices expectations, were derived from the interview. RHEA is applied to a coastal town in North Carolina, USA where data on both coastal amenities and flood risks affect locations choices and price dynamics.

The innovativeness of the current model is threefold: (i) in comparison to economic studies of land use (Irwin & Bockstael, 2002) RHEA explicitly simulates the emergence of property prices under adaptive price expectations of heterogeneous agents, including the emergence of cardinally new trends in prices and their spatial distribution, (ii) in comparison to other agent-based LMMs, which are stylized abstract models (Ettema, 2011; Gilbert, Hawksworth, & Swinney, 2009; Magliocca et al., 2011; Parker & Filatova, 2008), the current model makes a step forward toward empirical modeling of ABM land markets by using actual hedonic studies and distribution of households incomes; (iii) in comparison to other empirical spatial ABMs of urban phenomena (Brown et al., 2008; Robinson et al., 2007) RHEA has a full LMM with adaptive price expectations, which allows for the emergence of prices and may lead to qualitatively different trends in spatial patterns (Parker et al., 2011).

The primary goal of this paper is to provide the first detailed description of the RHEA LMM with a special focus on micro-foundations and methodological aspects related to merging theoretical and empirical approaches (Section 2). In addition, a series of experiments is presented to explore how the model's micro-foundations impact aggregated spatial urban system dynamics (Section 3). Conclusions and future work are outlined in Section 4.

2. Model description (ODD + D)

The RHEA LMM is described below employing the standard ODD protocol for ABMs (Grimm et al., 2010), which was recently extended to account for human decision making – ODD + D (Mueller et al., 2013).

2.1. Overview

2.1.1. Purpose

RHEA aims to provide a methodological platform to integrate adaptive economic behavior into the spatial landscape using urban economics theory and traditional data sources. This article presents the base model but specific experiments could be designed to explore a range of research questions that are difficult to tackle with other economic or geographic tools, which rely exclusively on static agents' behavior and past data (Filatova & Bin, 2013). In particular, how do changes in preferences or risk perceptions capitalize in property price? How do structural non-marginal shifts in land markets emerge from the bottom and propagate up to the top? How do economic land use systems react to climate change? RHEA allows direct modeling of interactions of many heterogeneous agents in a land market over a heterogeneous spatial landscape simplifying further coupling of economic models with ecological ones. As in other ABMs of markets, RHEA helps to understand how aggregated patterns and economic indices result from many individual interactions of economic agents (Tesfatsion, 2006).

[2] An open question interview was conducted in 2012 with L. Vidgop-Barg a practicing realtor with extensive experience.

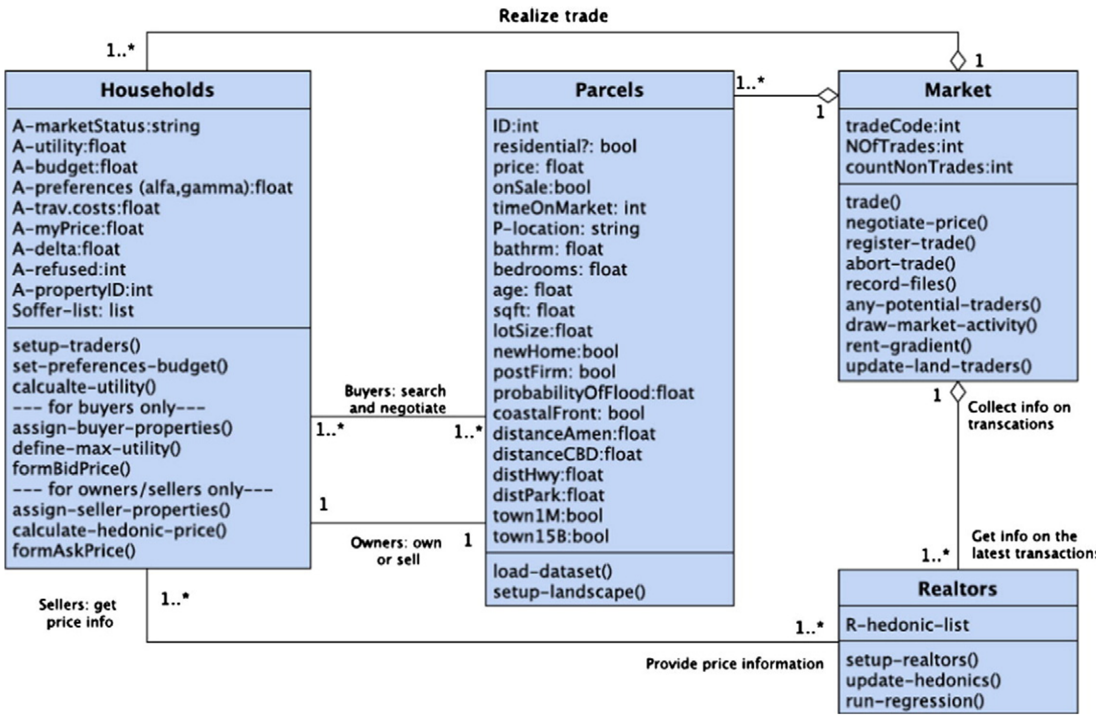

Fig. 1. UML class diagram of the bilateral housing market: agents, their properties and functions (Section 2.1.2). Associations between agents label either the nature of a relationship or the roles of agents. The multiplicity notations indicate when the instances of classes are related to each other as one to one ('1' and '1') or one to many ('1' and '1..*').

The model could be used by scientists to explore methodological questions (e.g. to compare the performance of various expectation formation algorithms with different information update time, and study the effects of agents heterogeneity (Huang, Parker, Sun, & Filatova, 2013) and by policy-makers to explore the extent of changes in economic system, e.g. in response to adverse consequences of climate change and impact of adaptation policies (Stern, 2008).

2.1.2. Entities, state variables and scales

The main agents in the model are households willing to buy and sell properties in a coastal city, real estate agents who observe market dynamics and form expectations, and parcels that can be residential or non-residential where the former represent spatial goods. The three types of agents are connected through the market (Fig. 1).

State variables that are used in this base model are listed in Tables 1–3.

The model is spatially explicit, using empirical GIS data from Bin et al. (2008) uploaded at initialization. The empirical landscape includes cadaster data on non-residential and residential parcels, as well as ocean and river areas. At initialization each residential property is populated with an economic agent. The size of residential parcels varies between 0.005 and 42.4 acres. The model operates on a spatial scale of one or few coastal towns. Technically, a larger spatial area can be represented but this slows down the simulation. One time step in RHEA is equal to 1 month.[3]

2.1.3. Process overview and scheduling

The main process in the ABM is trading of residential properties and allocation of households in a town. 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 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 Fig. 2. RHEA borrows some elements of the base trade flow logic of the ALMA model (Filatova, Parker, & van der Veen, 2009; Filatova, Parker, & van der Veen, 2011). As in ALMA, a simulation in RHEA starts with sellers putting properties on the market, while buyers select a property to bid on by finding a maximum-utility parcel under budget constrains. However, RHEA has several fundamental differences compared to ALMA. Namely, it employs new procedures: (1) to initialize sellers (box I, Fig. 2), (2) to account for empirical landscape and hedonic price function (box II and III), (3) to estimate utility function assuming substitutability between a housing and a composite good (box V), (4) to select the cheapest property among those with similar levels of utility (box VI), (5) to realize price negotiation procedure (box IX), and (6) to perform adaptive price expectations (box XII and XIII). The primary mechanisms that are innovative in RHEA compared to the rest of the field are the empirical setup of ask and bid prices, the introduction of realtor agents who update price expectations for heterogeneous spatial goods, and the detailed modeling of price negotiations.

2.2. Design concepts

2.2.1. Theoretical and empirical background

The RHEA model combines the microeconomic demand, supply, and bidding foundations of spatial economics with the spatial heterogeneity of econometric models in a single methodological platform. It models a coastal city where both coastal amenities and flooding disamenities drive land market outcomes, facilitating separate analysis of the effects of each driver on land rents. RHEA starts with a conventional urban economic model and gradually relaxes the assumptions of perfect rationality and homogeneity among households as well as the assumption of an instantly equilibrating land market. In particular, RHEA is grounded in a

[3] The decision to choose a 1 month time step is because households that decide to buy a house are likely to make several attempts a year. Besides realtors base their price expectations on the recent sales, i.e. 1–3 months, or up to 6 months or more if not enough trades happened in an area (interview with L. Vidgop-Barg).

Table 1
State variables related to the spatial landscape of RHEA.[a]

Variable name	Brief description	Value
I. Spatial landscape (GIS parcel data)		
ID	A unique ID of a GIS parcel (spatial good)	***
Residential?	Indicates whether a parcel is under residential or non-residential use	[0;1]
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	[0;1]
timeOnMarket	Counts the months which this parcel is for sale on a market	Endogenously determined
P-location	X and Y coordinates of a parcel	***
bathroom	Number of bathrooms	Uploaded from GIS dataset
bedrooms	Number of bedrooms	
age	Year house was built subtracted from 2004	
sqft	Total structure square footage	
lotSize	Total lot size measured in acres	
newHome	Dummy variable for new home (1 if sold within a year after built, 0 otherwise)	
postFirm	Dummy variable for post-FIRM properties (1 if post-FIRM, 0 otherwise)	
probabilityOfFlood	Probability of flooding (0, 1:100, 1:500)	
coastalFront	Dummy variable for the first row from coastal water (1 if on, 0 otherwise)	
distanceAmen	Distance in feet to the sound or Intracoastal waterways	
distanceCBD	Distance in feet to downtown Morehead City (town1 M)	
distHwy	Distance in feet to nearest highway	
distPark	Distance in feet to nearest park, forest, or game land	
town1 M	Dummy variable for a township (1 if Morehead, 0 otherwise)	
town15B	Dummy variable for a township (1 if Beaufort, 0 otherwise)	
kH	Coefficient that translates overall property price into an annual payment	1/15

[a] *Note*: here we list only those agents and their state variables, which are used for the simulations done for this paper. Other implementations of this model published elsewhere may have different state variables and values.

monocentric urban model (Alonso, 1964) enriched by coastal amenities following (Wu, 2006; Wu & Plantinga, 2003) and flood hazard probabilities following Frame (1998). Thus, spatial goods in this agent-based computational economics (ACE) market are quite heterogeneous differentiated by distance to Central Business District CBD (D), coastal amenities (A), probability of hazard (P) and structural housing characteristics. In RHEA heterogeneous household agents (buyers and sellers) exchange heterogeneous spatial goods (houses) via simulated bilateral market interactions with decentralized price determination. Empirical data are used to initialize spatial landscape, to parameterize agents' properties (Table 2) and to define the initial hedonic function (Bin et al., 2008), which real estate agents use for price predictions.

2.2.2. Individual decision-making

The household agents in the model are differentiated by their role (A-marketStatus in Fig. 1): buyers, sellers and inactive property owners. The latter are associated with a certain property but do not perform any actions[4] except eventually deciding to become a seller. The behavior of agents is explained below.

Sellers' behavior: 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, Fig. 2). 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 (F_{sale}) and its standard deviation is defined exogenously (Table 3). 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, a decision regarding which owners are actually going to become sellers has two alternative implementations. Specifically, they can either be selected randomly or be based on utility (Eq. (2)) – i.e. only the least-satisfied households become sellers. In either case, the final number of sellers is equal to the number of properties for sale. As the simulation goes on, settled households may decide to relocate following the selected seller choice strategy (either random or least-satisfied agents).

At the beginning of a trading period active sellers announce their **ask prices**. They do so by requesting regression coefficients from the hedonic analysis of the current period (box II, Fig. 2) and applying them to their property (box III). At the initialization stage this hedonic function and coefficients come from Bin et al. (2008). As the model runs and new transactions occur real estate agents are rerunning the hedonic analysis. Regression coefficients – i.e. willingness to pay for a specific attribute of a property of an average household in a current market – may change driven by the inflow of new households with different preferences for locations or potentially dynamic perceptions regarding flood risks. After buyers make their choices (boxes IV–VII, Fig. 2), all sellers check how many bid-offers they received. They choose the highest bid to engage in price negotiations (box VIII, Fig. 2). 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 2.2.6).

Seller's price formation (Section 2.2.3) 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 2.2.6). At the start of a seller's trading history, his D_{neg} is equal to one month 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 month of mortgage, i.e.:

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

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

Currently RHEA does not include modeling of developer's behavior. Thus, the pull of residential housing is constant.

Buyers' behavior: at the beginning of a trading period all active buyers start searching for a property that maximizes their utility

[4] For the next version of the model we plan to include other interactions, such as opinion exchange regarding risks, in which property owners who are not active seller yet will also participate.

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

II. Households (traders) – parent class		
A-marketStatus	A market status of a household agent in a current time step	Buyer, seller, traded
A-alpha	Household preference for a spatial good over a composite good. *Source*: (Heckbert and Smajgl 2005)	0.3
A-gamma	Household preferences for coastal amenities. *Source*: (Wu and Plantinga 2003)	0.5
fixedAlpha fixedGamma	Boolean, determines whether agents have homogeneous or heterogeneous preferences for spatial goods or environmental amenities	[0;1]
A-utility	Agent's utility for a specific spatial good	Eq. (3)
A-budget	Household annual income (empirical distribution/average empirical). *Source*: USA statistics[a]. The statistical data on income distribution for the Carteret county (NC) was available for 2011; to match the price levels of hedonic analysis the incomes were adjusted to 2004 prices using Consumer Price Index[b]	(8362–209,044)/51,939
A-trav.costs	Agent's travel costs per unit of distance. Source: (Wu and Plantinga 2003)	0.284
A-myprice	Stores the value of a bid or ask price agent is ready to pay for a certain parcel	Eqs. (6)–(8)
A-refused	Counts how many times an agent did not succeed in buying or selling a property	***
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 monthly rent	Endogenously determined
Bid price	Buyer's bid price for a specific spatial good	Section 2.2.2
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 monthly rent and grows with timeOnMarket	Eq. (1)
Ask price	Asking price the seller assigns to the cell he owns	Sections 2.2.2 and 2.2.3

[a] United States Census Bureau, http://factfinder2.census.gov/faces/nav/jsf/pages/index.xhtml.
[b] United States Department of Labor, http://www.bls.gov/cpi/.

Table 3
State variables related to real-estate agents and market in RHEA.

III. Real-estate agent		
R-hedonic-list	List of regression coefficients of a hedonic model in a certain time step, also serves as memory	Section 2.2.3
R-hedonics	Adaptive or statics	
R-learning-strategy	A strategy to update market expectations	
IV. Market		
fraction_on_sale (F_{sale}) sd_fraction_on_sale	Share of owners who decide to become sellers (mean and standard deviation)	0.25 0.02
SellerChoice	Method to define which owners become sellers	Random
NumberOfBuyers	Number of newcomers entering the market every time step	Equals to new sellers
tradeCode	The code, with which a trade attempt is marked	Section 2.2.6
NOfTrades	Number of trades	Endogenous

(boxes IV–VI, Fig. 2). Household's utility depends on a combination of composite (z) and housing (s) goods which is affordable for her budget (Y) net of transport costs ($T(D)$):

$$U = s^{\alpha} z^{1-\alpha} A^{\gamma}$$

or

$$U = s^{\alpha}(Y - T(D) - k_H H_{ask})^{1-\alpha} A^{\gamma} \tag{2}$$

Preferences for housing good (α) and amenities (γ) as well as exogenous incomes (Y) are heterogeneous across household agents.

When choosing a location in a costal town with designated flood zones, a household operates under the conditions of uncertainty. Thus, she in fact maximizes her expected **utility** (EU):

$$EU = P_i U_F + (1 - P_i) U_{NF} \tag{3}$$

where *UF* is the households utility in case of a flood event, *UNF* is utility in the case of no flood, and P_i is a subjective risk perception of a buyer. In economic literature individual, possibly biased, risk perception is often formalized by means of altering objective probability of flooding (P). Thus, $P_i = P \pm \Delta$ where Δ is an individual bias that can be changing over time.

$$U_F = s^{\alpha}(Y - T(D) - k_H H_{ask} - L - IP + IC)^{1-\alpha} A^{\gamma} \tag{4}$$

$$U_{NF} = s^{\alpha}(Y - T(D) - k_H H_{ask} - IP)^{1-\alpha} A^{\gamma} \tag{5}$$

Here *L* is the damage in the case of flood, *IP* is annual flood insurance premium, *IC* is insurance coverage in the case of a disaster. It is assumed that housing search is costly, thus, households do not search for a global maximum but explore a subset[5] of properties only, from which they select the one that delivers the highest utility. Thus, buyers do not operate under perfect information.

Buyers have subjective perceptions of flooding probability, which may be biased compared to the objective probability *P*. Risk perceptions could be made dynamic over time. The simulations reported in this paper use objective risk perceptions.

After a buyer has found the property that gives her the maximum utility, she submits her **bid price** to a seller (box VII, Fig. 2). Buyers bid differently depending on how long a property is on a market and on their relative market power (Eqs. (6), (7)). During the interview with the US realtor it became clear that a buyers' price is anchored to a sellers' one: buyers bid between 3% and 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:

$$\in [(H_{ask} - h);\ H_{ask}] \tag{6}$$

[5] The number is user-defined. In this simulation we used 10.

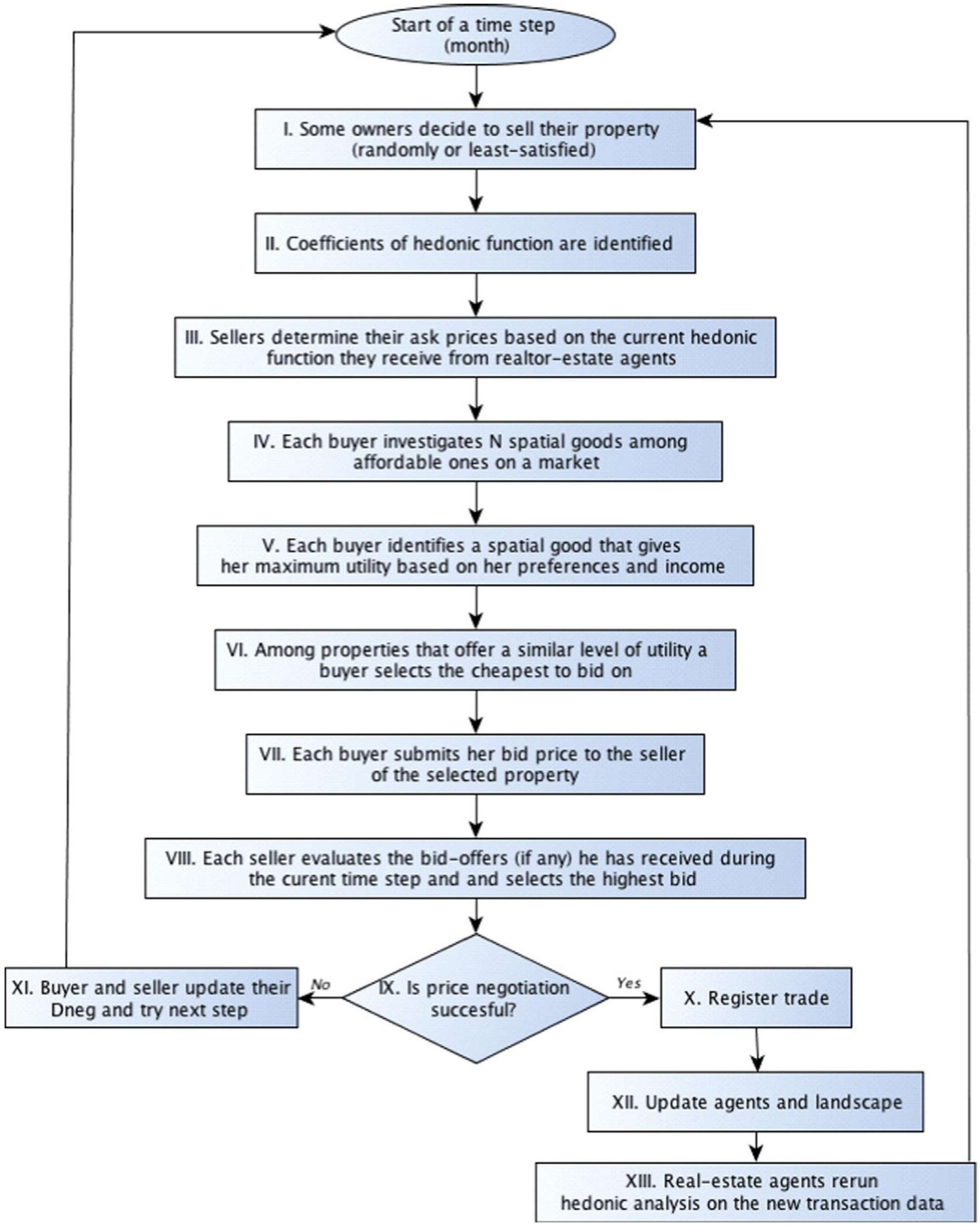

Fig. 2. Dynamics of the trade process: a sequence of actions, which agents perform within 1 time step of the bilateral agent-based housing market with expectations formation (Sections 2.1.3 and 2.2).

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

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.

$$H_{bid} \in [H_{ask};\ (H_{ask} + h)] \tag{7}$$

In the current implementation of the model the sign of h is determined randomly. RHEA departs from previous work (Filatova, Parker et al., 2009; Magliocca et al., 2011), which introduced a variable to represent a relative excess of supply or demand in a market, and by multiplication pushed housing prices up or down. Instead of formally imposing an increasing or decreasing price trend in the code, RHEA allows natural emergence of such a phenomena entirely through agents' interactions. Specifically, less attractive or overpriced properties get fewer bids and thus are more likely to get a decrease in price (i.e. competition between sellers). At the same time, a more desirable property in general attracts more buyers and is likely to have an increase in price since sellers would choose the highest bid (i.e. competition among buyers). 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 & Smajgl, 2005).

In case buyers are not able to find a property, which they like and are able to afford, they leave the town. It occurs after five unsuccessful trade attempts. This assumption seems reasonable since the scale of the model is one town with only 3588 residential properties, and it is logical to search elsewhere in the neighboring area.

2.2.3. Learning

One of the core decisions in decentralized ACE markets is the learning process regarding prices (LeBaron, 2006; Tesfatsion, 2006). It is challenging to model price expectations in urban property markets characterized by high heterogeneity of goods, which are infrequently traded. While ACE has made major progress in modeling markets of homogeneous goods (Arthur, Durlauf, & Lane, 1997; Kirman & Vriend, 2001; Tesfatsion & Judd, 2006) land is a good with very diverse attributes. The same house in a different location may have a disproportionally different price as do two houses with different structural characterizes in the same neighborhood. Modeling price expectations in housing markets needs an introduction of a mediator who learns the efficient price of any unique house and who often participates in transactions of such infrequently purchased goods as a house (Ettema, 2011; Gilbert et al., 2009; Magliocca et al., 2011; Parker & Filatova, 2008). As the mediator engages in many transactions, the society of agents relies on collective information about recent transaction prices. Thus, it is a collective learning process. The existing spatial ABMs that employ learning algorithms to support trading process in a land market (Balmann & Happe, 2000; Magliocca et al., 2011) deal still with relatively homogenous spatial goods, often differentiated only by the distance to CBD and size. The challenge here is to account for other attributes of housing, (up to 14 GIS attributes in our dataset including amenities and risks) that affect trading behavior.

Real estate agent and formation of price expectations: RHEA builds on previous research on agent-based LMMs and introduces real estate agents who observe successful transactions and form price expectations. 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 in an open-question interview with the US real estate agent.

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 14 GIS attributes (Table 1). 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):

$$\ln H_{tran} = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \varepsilon \tag{8}$$

Here $\ln H_{tran}$ is the log of transaction price, x_i is a variable for the ith housing attribute (structural, neighborhood and environmental), β are regression coefficients, and ε is the error term.

At initialization realtors are endowed with coefficients of the original hedonic analysis of Bin et al. (2008, Model 4). At the end of each time step, all successful transactions get registered in a file (trade.csv) together with all the attributes of traded agents and properties. Each month 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 3–12 trading periods. If the number of realized transactions is not sufficient to capture the variation on housing prices in the regression analysis, then the horizon is extended for another month. Regression analysis based on these recent transactions is realized by employing the R-extension of Netlogo (Thiele & Grimm, 2010), which makes it possible to have a direct coupling of R-scripts and the Netlogo ACE model. Eventually, the new coefficients got recorded into realtors memory. 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 2004 analysis (Bin et al., 2008) will be used throughout the whole simulation.

During the second stage of price expectations a real estate agent may decide to apply one of the price learning strategies to suggest the final asking price to a seller. Following Magliocca et al. (2011) RHEA uses four economic prediction models: mean, projection, mirror and regional models. Whether to activate or not the second stage of price expectation is determined by a user currently.

2.2.4. Individual sensing

Information about realtors' estimates of a property price 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 cells. Yet, at this stage the costs of information gathering by buyers are not explicitly included in the model. Sellers' ask prices are public information but a buyer is not aware of the bids other buyers make.

2.2.5. Individual prediction

Traders rely on pricing information, which realtors provide. The prediction involving learning algorithms is present only if real estate agents activate the second stage of expectation formation. If the latter is not activated, then agents make decisions based only on the current state of the landscape and the current market.

2.2.6. 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 a trade period (for details on b, c and d see Section 2.2.2 and Fig. 2). The outcomes of these interactions also indirectly affect future trades through real estate agents updating their price expectations (Section 2.2.3). Let us elaborate on the first type of interactions, as it constitutes one of the innovative aspects of the RHEA model. This type of interactions gets activated during the trade process (box IX Fig. 2).

Price negotiations in land market ABMs are often presented in a simplified way – as an arithmetic or geometric average between bid and ask prices. The RHEA model aims to bring in more realistic price negotiations procedure. Specifically, buyers and sellers do not simply settle on a price, which is an average of bid and ask, but rather play with their market power when negotiating. Moreover, during the interview with the US realtor it became clear that a buyers' price is always anchored to that of a sellers. Both prices are linked to the market average suggested by realtors. Yet, bids can vary because of the buyers or seller market or depending on how much a buyer wants the property. These processes are captured through competition on sellers' as well as on buyers' sides in the new price negotiation procedure (Fig. 3). Specifically, 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), Fig. 3). If the highest bid is below the original ask price, then the market power of agents plays a role (box (2) Fig. 3). 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 month for another trade attempt (her D_{neg}) are

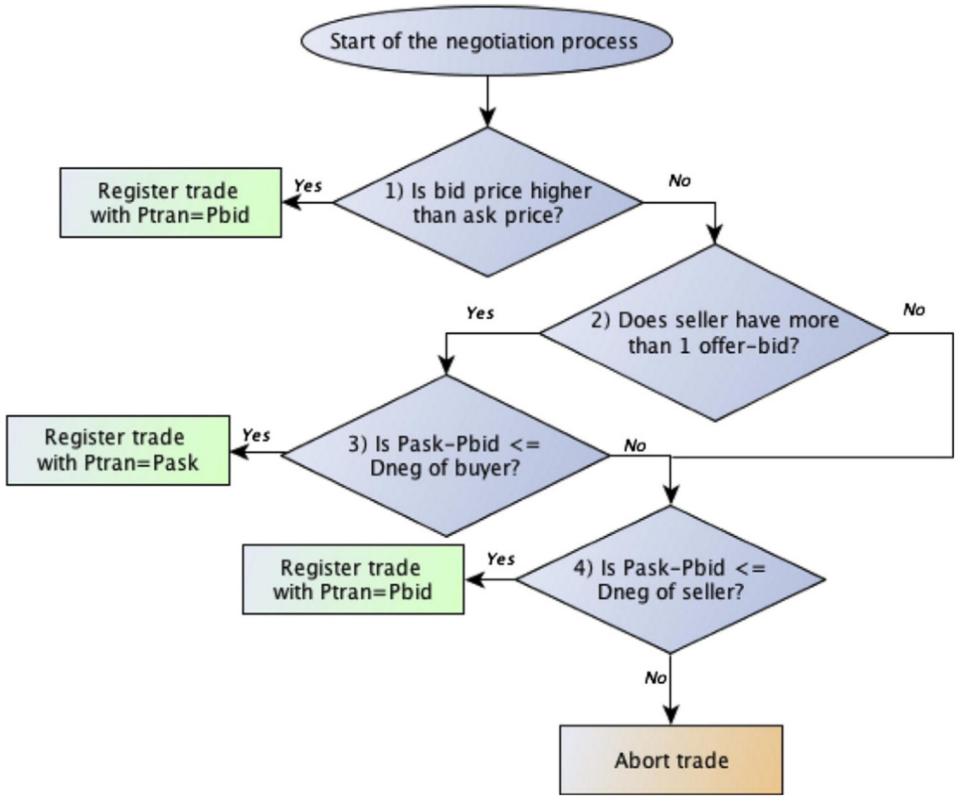

Fig. 3. The simulation flow of the price negotiation process (Section 2.2.6). Here: buyers' opportunity costs of waiting another month for another trade attempt (D_{neg} of a buyer) are equal to 1 month of rent, seller's opportunity costs of waiting another month (D_{neg} of a seller) are equal to 1 month of mortgage. Both of them are updated following unsuccessful trades.

comparable to the difference between the bid and ask prices (box (3) Fig. 3). Here D_{neg} of a buyer is operationalized as one month of renting an average house in the city,[6] 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 month 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) Fig. 3). In particular, he compares the difference between bid and ask prices to the opportunity costs of waiting another month (his D_{neg}) and accepts the bid price, if comparison is in its favor. The D_{neg} of a seller is operationalized as one month of mortgage for his property at the start of sellers trading history and gets updated with every unsuccessful trade attempt (Section 2.2.2). 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), Fig. 3, 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).

Considering the processes in Figs. 2 and 3 the overall trade process may result in the following outcomes, coded with 'trade codes' (Table 4).

2.2.7. Collectives

Agents do not form any networks or other collectives.

2.2.8. Heterogeneity

Traders can be heterogeneous in their preferences for spatial goods over composite and for coastal amenities, in their risk perceptions and in their budgets. To explore research questions at hand RHEA allows setting up combinations of sources of heterogeneity as well as initiating homogenous agents by varying parameters such as A-budget, fixedAlfa/Gamma and their average values (Table 2).

Buyer, seller and real estate agents have different decision-making rules, as elucidated in 2.2.2 and 2.2.3 above.

2.2.9. Stochasticity

When the population of agents is created as heterogeneous in their attributes (preferences, risk perceptions, incomes) during initialization and consequent steps (for incoming buyers), specific values of those attributes are assigned randomly to agents. Moreover, during the model run, irrespectively of whether traders activated during the simulation are heterogeneous or homogenous, the randomness comes in when property owners decide to become sellers (if random strategy is chosen), when buyers set up their bid prices, and when the number of incoming households is determined every step.

2.2.10. Observation

Urban property prices emerge as a result of bilateral trades between buyers and sellers with diverse incomes and specific preferences in a heterogeneous landscape. This can be reflected on a map as a color-gradient of property prices changing over time. Furthermore, RHEA monitors a set of macro-scale measures such as total property value in the area, average rent in a city, average price in a non-flooded vs. hazard-prone areas, and aggregate utility of settled households. These aggregated outcomes are important for the understanding of price dynamics as people with different incomes and preferences arrive to the studied areas, and for tracing agents' welfare over time.

Moreover, at the end of each time step there are a number of tables (csv files), which get updated. Specifically, each trade attempt (successful and unsuccessful) gets recorded in the trade.csv table together with all attributes of the buyer and the seller and the property in question, what allows running new hedonic analysis when needed. In addition, realtors record their current regression coefficients of hedonic model

[6] 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 monthly rent would be heterogeneous across households.

Table 4
A list of 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 month
TC7	Trade does not occur because there were no bids offered to a seller

in the realtors.csv file, so that the dynamics of price expectation formation can be traced over time.

2.3. Details

2.3.1. Implementation details

The model is implemented in Netlogo v5.0.4 (Wilensky, 1999) using GIS[7] and R (Thiele & Grimm, 2010) extensions. R-scripts are called from within Netlogo during each time step. The model will be accessible via OpenABM.org at the end of the project (2015–2016).

2.3.2. Initialization

The model is initialized with either two coastal cities in North Carolina, USA, or only one of them (Beaufort or Morehead) with 34,923, 7106 or 24,980 GIS parcels, respectively. About half of those parcels are residential, other represent water or undeveloped areas. The number of residential owner-agents at initialization for e.g. Beaufort city is 3588, the number of sellers and buyers is user-defined. The properties going for sale at initialization vary across model runs. The incomes, preferences and risk perceptions of household agents are set at initialization according to the user settings (see Sections 2.2.8 and 2.2.9).

2.3.3. Input data

In this paper RHEA is applied to the coastal town of Beaufort. The area is in general low lying and is prone to flooding with probability of 1:100 and 1:500 in certain zones. At initialization RHEA uploads vector data from multiple GIS data-sets on the locations of residential housing, coastal amenities (measured in terms of distance from coastal water and sound, and a Boolean measure of waterfront), flood probabilities, distances to the CBD and national parks, and data on structural characteristics of properties (Table 1). Distance to CBD in the GIS dataset is measured as the distance to the nearest main employment center in the area – a neighboring town Morehead (Bin et al., 2008). In addition at initialization realtor-agents get the empirical hedonic function (Bin et al., 2008) based on the real estate transactions from 2000 to 2004 after a period of active hurricane seasons from middle of 1990s to 2003. Data on households' incomes and preferences is taken from various sources (Table 2).

2.3.4. Submodels

The submodels described in Fig. 2 are explained in detail in Section 2.2.

3. Results

3.1. Experiment settings

The experiments presented here are for the city of Beaufort, USA (Fig. 4). The area in our GIS dataset contains 7106 parcels, 3588 of which are residential. Among residential parcels 50% are located in the zone with zero flood occurrence, 27% and 23% of residential properties are in 1:100 and 1:500 zones respectively. The characteristics of residential parcels vary as described in Table 5.

To test the effect of various micro-foundations five experiments were run (Table 6). The first experiment serves as a benchmark, i.e. the most simplified micro-foundations of agents' behavior are used. It demonstrates the behavior of a representative agent without any adaptation. Further experiments introduce the heterogeneity of agents in disposable incomes, which comes from statistical data. Then heterogeneity in preferences and adaptive price expectations are gradually added.

3.2. Observation on micro-foundations #1: introducing empirical data into the landscape and agents' behavior

RHEA attempts to bring together theoretical micro-foundations of urban economics and traditionally available empirical data. A major challenge on this path toward empirics is that one needs to use various sources of data: aggregated (e.g. incomes here) and micro-level data (individual property prices), data for a specific geographical location (parcel-level data) and average country level data (preferences for spatial goods over composite goods or for amenities). When various data sources are merged in an agent-based market it is quite likely that trader-agents endowed with certain preferences and incomes may not necessary represent the population that was active on the actual coastal property market during the period, for which hedonic analyses and consequently housing prices are estimated. Thus, an ACE market would need to adjust the empirically-defined demand function, i.e. hedonic function, with the simulated demand that emerged from individual demands of agents endowed with empirical data from other sources. As Fig. 5 demonstrates in RHEA it happens primarily during the first time step when all prices jump significantly, even in the base case of fully homogeneous traders and static realtors in Exp1, to catch up with the current simulated demand. Modifications in traders and realtors behavior as well as spatial heterogeneity (average prices in safe, flood-prone and waterfront zones) may affect the extent of this sharp change in price but not the fact of its occurrence (Exp2–5, Fig. 5). The prices for the most demanded properties – coastal front properties – adjust quicker than for less attractive zones as a result of endogenous housing market.

Let us consider price dynamics variation for four general types of properties: average price of properties located in the safe zone (Fig. 5a), in the zone with 1:100 chance of flood occurrence (Fig. 5b), in the areas where probability of flooding is 1:500 years (Fig. 5c), and for waterfront properties (Fig. 5d). It should be noted that there are overlaps between some categories as waterfront properties may be either in a safe or 1:100 flood zone. On average the level of amenities (measured as proximity to the coast and availability of the coastal front) in the areas with 1:100 flood occurrence are 45% higher than in the safe one while in 1:500 flood zone amenity levels constitute only 48% of amenity levels in the safe zone. A market with homogeneous traders and static realtors (Exp1) produces quite stable price trends over the first three categories of properties except for the coastal front properties. As preferences for coastal amenities are quite strong, the demand for these areas is the highest and the market constantly adjusts by

[7] GIS extension of Netlogo: http://ccl.northwestern.edu/netlogo/docs/gis.html.

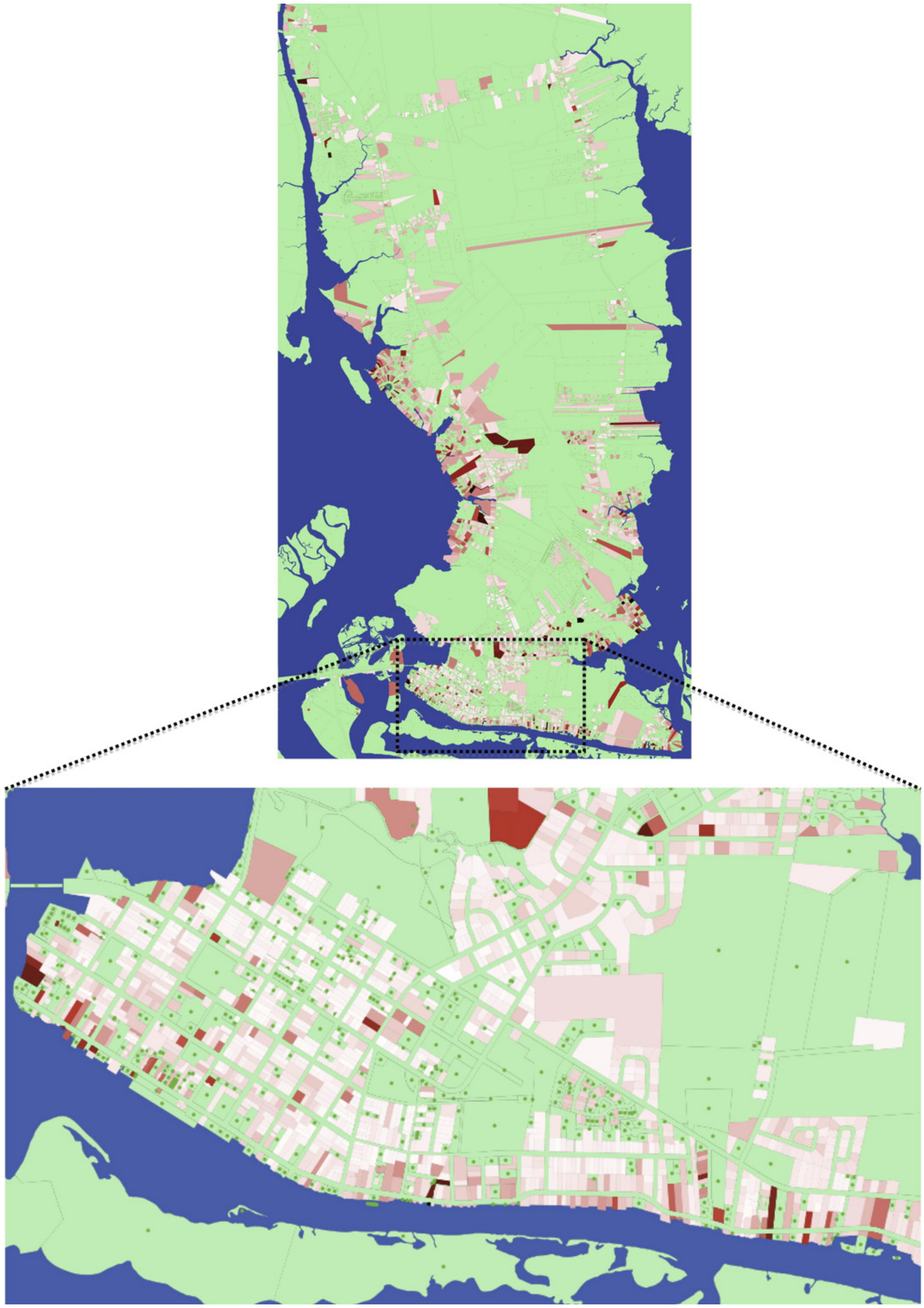

Fig. 4. A map of property price gradient at initialization (Beaufort coastal town, North Caroline, USA). The darker the red color the higher a property price is. Green color symbolizes non-residential properties; blue color stands for ocean.

pushing prices up. Prices for properties in areas with 1:100 years flood occurrence are higher than in safe areas: between 4% (in Exp2 and 4) and 12–16% (in Exp5 and 3) price increase in 1:100 zone compared to 2% (in Exp2 and 4) and 7–11% (in Exp5 and 3) price increase in the safe zone (Fig. 5b vs. 5a). Properties in 1:100 zone have higher level of coastal amenities compared to safe and more landward properties: 207 out of 975 parcels in 1:100 flood zone are waterfront compared to only 199 waterfront properties among 1777 ones in the safe zone. As Bin et al. (2008) demonstrated in their hedonic analyses marginal willingness to pay for amenities is higher than marginal price discount for risk. One may also notice that price trends in the flood zone of 1:500 years is controversial in markets with adaptive price expectations (Exp3 and 5 in Fig. 5c) but has a clear downward trend in markets with heterogeneous agents and static expectations (Exp2 and 4, Fig. 5c). Properties with a flood occurrence 1:500 years have lower expected utility than comparable properties in safe zone and at the same time the level of environmental amenity is low (only 2 out of 408 properties are waterfront) what makes them less attractive than 1:100 zone properties. The relatively low demand for those areas leads to a decrease in the price trend.

Table 5
Heterogeneous attributes of housing goods in the GIS data set.

GIS parcel attribute	Min	Average	Max
Number of bathrooms	0.5	1.7	6
House age	1	38.45	103
Sq. footage of a house	160	1581.2	4382
Lot size	0.005	0.92	42.39
Whether a house is in 1:100 flood zone	0	0.27	1
Whether a house is in 1:500 flood zone	0	0.23	1
Whether a property is at coastal front	0	0.11	1
Distance to amenity	1.8	1589.04	8445.6
Distance to CBD	7552.7	22781.9	69386.6
Distance to highway	50.7	2685	31313.3
Distance to parks	4331.9	14,412	36527.6

3.3. Observation on micro-foundations #2: heterogeneity vs. homogeneity

Introduction of heterogeneity among traders leads to more successful trade pairs. In particular, there is a better match between heterogeneous preferences for amenities as well as heterogeneous incomes and available spatial goods compared to the choice a representative agent faces (compare Exp2 to Exp1 in Fig. 6). Introduction of an empirical distribution of budgets rather than an average budget for whole population of traders adds more flexibility to satisfy agents' needs (compare Exp4 to Exp1 in Fig. 6), especially when preferences are also heterogeneous (Exp4 and Exp2, Fig. 6).

Systematic test for the impacts of heterogeneity in budgets and preferences in ABM LMMs have been performed and proven important for

Table 6
Variation in the model settings among experiments.

Experiment #	Preferences for amenity, A-gamma	Household annual income, A-budget	Realtor price update, R-hedonics
Exp1	Homogeneous	Homogeneous	Static
Exp2	Homogeneous	Empirical distribution	Static
Exp3	Homogeneous	Empirical distribution	Adaptive
Exp4	Heterogeneous	Empirical distribution	Static
Exp5	Heterogeneous	Empirical distribution	Adaptive

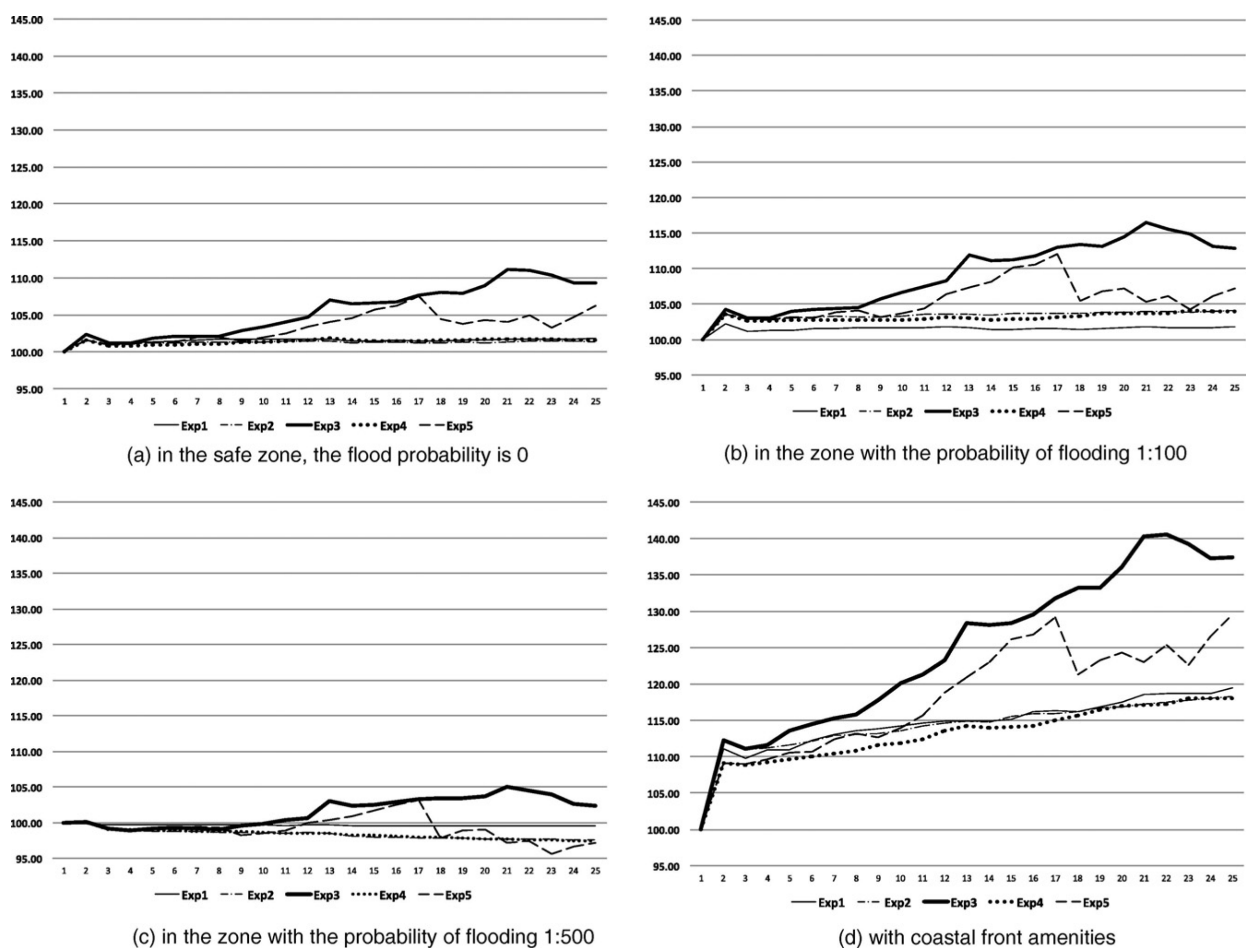

Fig. 5. Average price of a residential property over time under various settings. Specifically: Exp1 assumes buyer and seller agents having homogeneous incomes and homogenous preferences for amenities, realtors do not update price expectations based on the recent sales; Exp2 assumes buyer and seller agents having empirically-parameterized incomes and homogenous preferences for amenities, realtors do not update price expectations based on the recent sales; Exp3 assumes buyer and seller agents having empirically-parameterized incomes and homogenous preferences for amenities, realtors update price expectations based on the recent sales; Exp4 assumes buyer and seller agents having empirically-parameterized incomes and heterogeneous preferences for amenities, realtors do not update price expectations based on the recent sales; and finally Exp5 assumes buyer and seller agents having empirically-parameterized incomes and heterogeneous preferences for amenities, realtors update price expectations based on the recent sales.

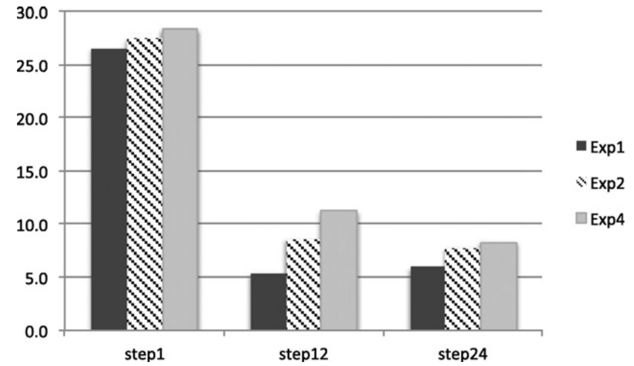

Fig. 6. The percent of successful trades (trade codes TC1, TC2, TC3 and TC5, see Table 4) in the total number of trade attempts over time.

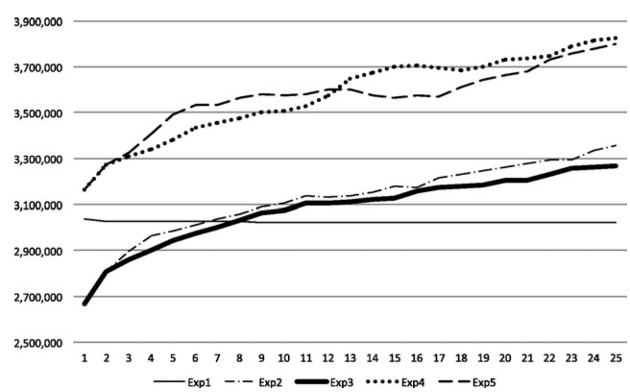

Fig. 7. Dynamics of the average utility of settled household agents in the city over time.

the resulting spatial patterns and economic metrics (Huang, Parker, Sun et al., 2013; Sun et al., 2014) as well as for the overall efficiency of a market (Heckbert, 2011). In RHEA heterogeneity in both budgets and preferences for amenity significantly affects utility of an average household who settled in the city. Specifically, in Exp1 – homogeneous preferences and budgets – average utility remains almost stable throughout a simulation (Fig. 7). As soon as empirical distribution of incomes in Exp2 and Exp3 is introduced the average utility starts growing over time. This happens because heterogeneity in budgets allows the market to sort agents across parcels with a distribution of prices in a way that maximizes their utility. Thus, budget heterogeneity is essential when modeling markets of heterogeneous goods with high price variability. Exp4 and Exp5 add preference heterogeneity on top of budget heterogeneity. As a result average utility in the city grows for another 15% due to the fact that traders with heterogeneous preferences are able to find a better match for their needs on a market. Activation of adaptive vs. static price expectations does not have a significant impact on average utility of settled households agents (compare Exp2 to Exp3 or Exp4 to Exp5 in Fig. 7).

3.4. Observation on micro-foundations #3: static vs. adaptive price expectations

RHEA implements a process of price expectations formation either as an adaptive (Exp3 and 5) or as a static one (Exp1, 2 and 4). When adaptive price expectation is activated a real estate agent monthly updates his hedonic function using R-extension based on the recent transactions. Table 7 presents the coefficients of a hedonic function changing over time for selected time steps.

The effect of these changes may be best seen visually in Fig. 8, which applies the static and adaptive hedonic model to an average house in the city. It is quite obvious that under adaptive expectations with an intensive trading the price of an average house is quite volatile.

Price dynamics for the four groups of properties in Fig. 5 also demonstrates that a housing market with no price update, i.e. 'static', has a very smooth price trend. At the same time a market with adaptive price expectations, which updates over time based on the recent transaction and preferences and incomes of newcomers, is quite corrugated. The level of 'bumpiness' depends on the interactions between landscape heterogeneity and micro-foundation of agent behavior. Specifically, in Fig. 5a and b the growth of the price trend under the adaptive realtor strategy (Exp3 and 5) is larger in the extent and is quite jagged compared to the small gradual increase in prices in markets with static realtor behavior (Exp1, 2 and 4). Fig. 5d shows that it is the extent and the speed of price increase that is higher in the adaptive price expectations markets (Exp3 and 5) in comparison with static ones (Exp1, 2 and 4). Thus, prices in highly demanded areas, e.g. waterfront here, experience an amplification effect if adaptive price expectation is activated. It implies that an assumption that base prices remain the same over time, i.e. realtors do not update their price information, is sufficient for modeling gradual change processes in housing markets. Impacts of abrupt

Table 7
Dynamics in the coefficients of the hedonic price function (Eq. (8)).

	Exp1, 2 and 4 throughout the simulation; Exp3 and 5 in time = 0	Exp3		Exp5	
		Time = 12	Time = 24	Time = 12	Time = 24
time	0	12	24	12	24
intercept	11.337	11.304	11.659	11.403	11.748
bathrooms	0.108	0.140	0.135	0.106	0.161
bathrooms^2	−0.011	−0.015	−0.003	−0.002	−0.002
age	−0.01	−0.008	−0.007	−0.011	−0.008
age^2	0.000094	−4.54E−06	−1.30E−06	1.22E−05	1.11E−06
SQFT	0.001	9.60E−04	9.64E−04	9.55E−04	8.56E−04
SQFT^2	−0.00011	−1.30E−08	−4.00E−09	−2.50E−08	−1.10E−08
lotsize	0.03	0.037	0.064	0.037	0.091
lotsize^2	0.00019	−4.23E−05	−4.43E−04	0.000058266	−8.18E−04
newhome	−0.059	−0.056	−0.054	−0.045	−0.041
postFirm	−0.022	−0.001	−0.006	−0.082	−0.058
FP100	−0.078	−0.058	−0.051	−0.062	−0.065
FP500	−0.062	−0.049	−0.044	−0.056	−0.059
coastalFront	0.314	0.372	0.378	0.354	0.377
log(distAmen)	−0.106	−0.101	−0.116	−0.115	−0.125
log(distCBD)	−0.00038	−0.015	−0.090	−0.022	−0.090
log(distHwy)	0.005	−0.002	0.007	0.001	0.004
log(distPark)	−0.001	0.001	0.035	0.021	0.044

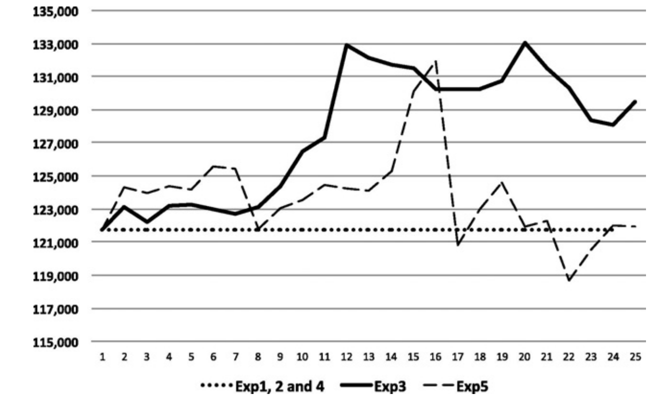

Fig. 8. Price of an average house in the town over time under static (Exp1, 2 and 4) and adaptive (Exp3 and Exp5) price expectations (in 2004 $). The regression function (Eq. (8)) with the current regression coefficients (Table 7) was applied to a house with average characteristics (Table 5).

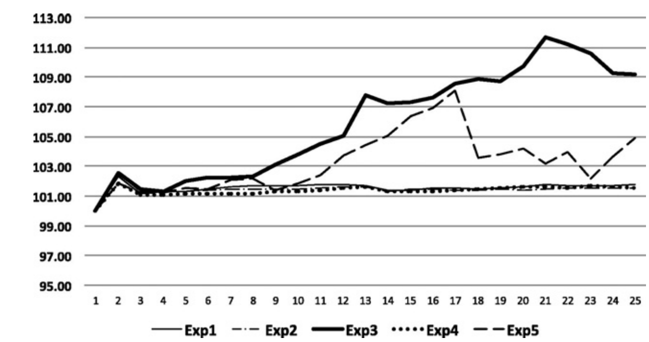

Fig. 9. Dynamics of total property value (in % from the value at initialization) in the coastal city under various micro-foundations of agent behavior (Exp1–5 in Table 6).

changes in markets and effects of social amplification, e.g. realized through market competition for highly demanded areas and reflected in prices trends, are evident when adaptive price expectations are present.

The aggregated effect of this dynamics is also well reflected in the trend of the total property value in the city (Fig. 9). The trend of the total property value in the city is bumpy in adaptive price markets (Exp3 and 5) and is smooth in static price markets (Exp1, 2 and 4). Accumulative effect of the adaptive vs. static price expectations is a distinct increase in property values over time, and thus an increase in a tax base for local governments as well as increase in direct expected damage if a flood disaster hits.

4. Conclusions

This paper provides a detailed ODD + D description of a spatially-explicit empirical housing market ABM – RHEA and demonstrates its performance under various micro-foundations. RHEA is well grounded in economic theory and uses readily-available spatial data and economic empirical analysis. It moves beyond existing work by making a step forward toward empirical modeling of ACE land markets by using actual hedonic studies and real distribution of households incomes, while explicitly simulating the emergence of urban property prices and their spatial distribution under adaptive price expectations of heterogeneous agents. The use of empirical data to parameterize micro behavior and validate macro patterns in ABMs is widely discussed (Heckbert, Baynes et al., 2010; Heckbert & Bishop, 2011; Robinson et al., 2007; Smajgl et al., 2011; Windrum et al., 2007). It is a challenge to employ empirical data while still grounding an ABM in a particular theory. Usually a modeler faces a trade-off between designing a theoretically-grounded model with no empirical data employed and a comprehensive empirical model but with ad hoc assumptions (Boero & Squazzoni, 2005). It is particularly difficult to keep empirical ABMs connected to a certain disciplinary theory, as one of the main reasons for using an ABM is to depart from certain stylized assumptions in a field. RHEA makes a step forward by marrying theoretically-grounded micro-foundations with standard empirical data.

The RHEA results demonstrate that this combination of theoretically sound micro-foundations in agents' behavior and empirical data is feasible and opens opportunities to explore various methodological and policy-relevant research questions. In particular, RHEA allows exploration of gradual as well as abrupt changes in spatial economic systems enabling possibilities to trace non-marginal abrupt shifts in housing market dynamics in hazard-prone areas when either changes in the environment or in agents' behavior occur. This is especially relevant for designing policies in the world with climate change where sudden non-marginal changes in economic system are expected. Existing decision-support tools are designed to tackle marginal changes only and may be misleading if economic systems undergo structural changes. The methodological setup of RHEA is not limited only to urban models. It can be extended to other challenges faced by decision-makers designing policies to manage coupled socio-environmental systems and by researchers modeling those.

Another advantage of RHEA is that while using empirical data, it maintains the flexibility of replacing it with stylized data if the former is missing. Moreover, RHEA does not rely entirely on historic data, which in fact represent only a snapshot of past choices in a land market, but is able to adjust with time. This functionality is enabled through incorporating adaptive expectations about land market dynamics into the spatial landscape. At the same time RHEA is programmed in open-access Netlogo software, a user-friendly and easy-to-learn ABM environment, which opens RHEA to a broad user community. The Netlogo code of RHEA empowered by the use of GIS and R-extensions facilitates real policy decision support. In summary, while many ABMs remain stylized and focus on exploration of methodological questions, RHEA deeply integrates micro-economic foundations with real data and standard empirical economic analysis. Thus, it represents an important modern trend in the ABM field: moving from stylized modeling experiments to simulating real life situations using data to their full extent.

Yet, the downside of this process is that by trying to match reality one makes a model increasingly more complex. This is known as Bonini's Paradox (Voinov, 2008): as a simulation model moves toward representing the complexity of a real system, it forgoes its comprehensibility and transparency. Thus, while the realism of a spatial ABM increases the complexity of micro-foundations in agents' behavior may need to be reduced. Robinson et al. (2007) also highlight that the ABMs using GIS data should be simple. This may perhaps imply that the use of state-of-the-art methodological advances in ABM and ACE, e.g. advanced artificial learning techniques, is challenging outside of a simplified context. In any case, RHEA is still data-intensive compared to stylized ABMs of spatial economic systems and may take time to calibrate to a new case study. Another limitation of this first presentation of the RHEA model is that a thorough validation and a comprehensive sensitivity analysis is still a subject of future work. A basic sensitivity analysis and comparative statics analysis is presented in Appendix A. Systematic sensitivity analysis of certain micro-foundations of agents and markets behavior is a vital aspect, which requires intensive simulation runs and development of techniques to manage big simulation-output data varying in time and space.[8]

The development of the RHEA model is the first stage of a multi-year project. While some limitations exist, often relevant for any type of

[8] The processing of big data from social science ABMs is a vital research frontier and is a subject of future work, for example within the MIRACLE project funded by the 'Digging Into Data' program http://wici.ca/new/research/digging-into-data-did-research/.

modeling, RHEA offers much potential. Future work can develop in several directions. Firstly, a detailed sensitivity analysis is to be performed, and in particular mutual effects of combining two parts of price expectation formation (Section 2.3.3) are to be studied systematically. Moreover, one needs to asses the realism of produced price patterns: while almost stable price trends in Exp1, 2 and 4 are hardly realistic, the abruptness of the corrugated dynamics of prices in Exp3 and 5 may also be exaggerated. Whether these market fluctuations are temporary or persistent can be important for interpretations and further applications of the model. The oscillations in price dynamics largely depend on the speed of information update, i.e. the intensity of monthly trades. Thus, sensitivity to the rates of buyers and sellers inflow, their trade intensity and the time-horizon of realtors should be studied. Secondly, agents, which are designed to make decisions under uncertainty following expected utility approach, can be compared with agents operating according to the prospect theory paradigm (Kahneman & Tversky, 1979). Thirdly, an introduction of individual risk perception evolution based on the theories of opinion dynamics (Acemoglu & Ozdaglar, 2011) in addition to adaptive price learning dynamics is of great interest. While majority of economic models assume static preferences and risk perceptions, agents do in fact learn to adjust their perceptions and preferences individually and through peer-to-peer networks (Janssen & Jager, 2001), and potentially make different choices. It has been demonstrated that alteration in agents' preferences may significantly change emergent outcomes of an ABM (Heckbert, Adamowicz et al., 2010). Lastly, a design and conduct of parallel experiments with human subjects in the lab and RHEA is planned. Lab experiments could be used to acquire behavioral foundations about risk perception dynamics in a group (Contini, Leombruni, & Richiardi, 2007), also when hazard probabilities change. ABM will help to extend these behavioral patterns to larger (than in the lab) temporal and spatial scales (Duffy, 2006; Heckbert, Baynes et al., 2010; Janssen, Holahan, Lee, & Ostrom, 2010; Poggio et al., 1999) and to validate agents' decision-making in a spatial landscape (Evans, Sun, & Kelley, 2006; Heckbert & Bishop, 2011). The work in these directions will increase the reliability of the RHEA model and improve its utility in supporting policy-making.

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Appendix A. Basic sensitivity analysis

Experiments 1–5 (Table 6) in fact present a sensitivity analysis of the model's emergent outcomes in terms of utilities, prices and their spatial distributions, on micro-foundations. This series of five experiments starts with a stylized case and moves toward more empirical representation of agents' behavior. Experiment 1 is a stylized base case scenario when neither budgets nor preferences of households' agents vary, and when expectations of future housing prices are not updated. Experiment 5 employs empirical distribution of households' budgets, assumes that preferences for amenities are normally distributed, and allows realtors to update price expectations based on recent sales. Yet, there are still several parameters, which have an impact on the emergent macro outcomes.

In what follows, we perform an additional sensitivity analysis of the model's macro-outcomes to several main micro-foundations. A comprehensive sensitivity analysis of the model performance, analysis and visualization of the 'big data' that it generates is currently under way.[9] Here we employ the comparative static analysis of agents' utility, link these trends to the impact on prices, and complement it with the examples of the model performance. We would like to highlight once again that households in RHEA make their purchasing decisions in a housing market in two stages: (1) they first select which house they like based on highest utility among considered houses, (2) then they decide what bid price to offer using seller's ask price as an anchor. Such a market design allows combining theoretically-grounded behavioral rules (i.e. resuming the standard setup of urban economics models in our case) with conventional empirical data (e.g. econometric hedonic model) to parameterize micro-foundations of agents' behavior while preserving agents and landscape heterogeneity. Yet, it also implies, that there is no formal link in equations between agents preferences, budgets and eventual transaction prices as it is replaced by logical expressions (i.e. if-else conditions) and filters (e.g. choosing minimum and maximum) in the program code. Given the architecture of this market, there is a direct link between agents' preferences and budgets and their utilities. The impact on prices is consistently related to changes in utility: the houses that are most desirable receive more bids (both below and above ask price), and have a higher probability to be sold above initial ask prices as sellers have an opportunity to choose the highest bid.

To derive qualitative predictions of how macro indicators of interest change with some exogenous parameters change, we performed "comparative statics" analysis by estimating first-order derivatives[10] of corresponding equations with respect to a certain parameter, while holding others constant.

A.1. Sensitivity to the years of mortgage

Coefficient kH translates the property price (H_{tran}) into an annual payment in Eqs. (1) and (2). Experiments in this paper make a simplifying assumption that mortgage is paid out in $m = 15$ years (i.e. $kH = 1/15$). If mortgage can be arranged for a longer/shorter period then it changes $Dneg$ of traders and their utility:

$$\frac{\partial D_{neg}}{\partial m} = -\frac{H_{tran}(1 + N_{USTr})}{12m^2} < 0 \tag{A.1}$$

If years of mortgage grow, i.e. kH decreases, then $Dneg$ of sellers decreases. This implies that opportunity costs of waiting another month are smaller and sellers can afford to wait longer for a better deal on a market. In other words they are more likely to reject option 4 in price negotiations (Fig. 3). Overall it means less successful trades in one time step or slower dynamics of a market, which in turn affects price expectations update. The direction, in which the latter changes, depends on several other factors: preferences of the incoming new buyers on a market, whether realtors extend the period of transaction analysis for more months, the types of properties that were sold recently and etc.

$Dneg$ of buyers is a monthly update of an average mortgage. Thus, if years of mortgage increase, i.e. kH decreases, then $Dneg$ of buyers also decreases. It implies that it costs less for buyers to wait resulting in less successful trades per trade period.

$$\frac{\partial U}{\partial m} = \frac{s^{\alpha} \cdot A^{\gamma} \cdot H_{ask} \cdot \left(Y - T(D) - \frac{H_{ask}}{m}\right)^{-\alpha}}{m^2} > 0 \tag{A.2}$$

[9] Please see details on the transnational Digging into Data MIRACLE project http://wici.ca/new/research/digging-into-data-did-research/.

[10] All derivatives were estimated using https://www.wolframalpha.com. The negative sign of a derivative implies that a macro variable declines with an increase in one unit of a parameter; the positive sign implies that a macro variable increases as a parameter grows.

Table A.1
Percentage difference in buyers' opportunity costs of waiting for another trade attempt in the next time step (*Dneg*) and in the average utility of settle households (*U*) in case years of mortgage change from 7 to 15 to 30 years. Coefficient $kH = 1/15$ (i.e. years of mortgage $m = 15$) is taken as the base case.

	Exp1			Exp5		
	$kH =$ 1/7	$kH =$ 1/15	$kH =$ 1/30	$kH =$ 1/7	$kH =$ 1/15	$kH =$ 1/30
Dneg of buyers	148.9	100.0	74.9	140.2	100.0	76.4
Average utility of settled households	86.6	100.0	107.2	94.2	100.0	106.0

Table A.2
Percentage difference in total property value in the modeled town and in the average utility of settle households (*U*) in case travel costs change from \$0.142 to \$0.284 to \$0.568 per foot per year. Coefficient $T = 0.284$ is taken as the base case.

	Exp1			Exp5		
	$T = 0.284/2$	$T = 0.284$	$T = 0.284 * 2$	$T = 0.284/2$	$T = 0.284$	$T = 0.284 * 2$
Total property value in town	99.6	100.0	99.4	98.9	100.0	106.1
Average utility of settled households	107.2	100.0	84.7	107.6	100.0	92.6

Table A.3
Percentage difference in total property value in the modeled town and in average rent buyers pay (buyers' *Dneg*) in case deviation of bid price from ask price changes from 3% to 5% to 10%. Coefficient $h = 5\%$ is taken as the base case.

	Exp1			Exp5		
	$h = 0.03$	$h = 0.05$	$h = 0.1$	$h = 0.03$	$h = 0.05$	$h = 0.1$
Total property value in town	99.6	100.0	99.9	99.8	100.0	165.7
Average rent (*Dneg* of buyers)	99.6	100.0	99.9	99.8	100.0	165.7

Table A.4
Percentage difference in the average utility of the settled households (*U*) in case standard deviation from the average preference for environmental amenities changes from 0.01 to 0.05 to 0.1. Coefficient $g = 0.05$ is taken as the base case.

	Exp4			Exp5		
	$g =$ 0.01	$g =$ 0.05	$g =$ 0.1	$g =$ 0.01	$g =$ 0.05	$g =$ 0.1
Average utility of settled households	87.7	100.0	161.6	87.8	100.0	159.6

If mortgage is given for longer period, i.e. years of mortgage *m* grows, then utility *U* grows because households either spend less on the same housing annually and have more disposable budget for a composite good, or can afford buying a more expensive house with bigger sq. footage or land lot or richer environmental amenities.

We run RHEA with $kH = 1/7$ and $kH = 30$ in addition to the base case of $kH = 1/15$ reported in the paper. We report the sensitivity of *Dneg* and *U* for experiments 1 and 5 as they present two extreme cases in terms of other settings (Table A.1). Changes are indeed in the direction predicted by Eqs. (A.1) and (A.2).

A.2. Sensitivity to travel costs

Currently travel costs per unit of distance are taken from another study (Wu and Plantinga, 2003), which provides an estimate of the real travel costs an average US household spends per year (\$1500 per mile per year or \$0.284 per foot per year). As travel costs per unit of distance may change, we find the first derivate of utility:

$$\frac{\partial U}{\partial T} = -s^{\alpha} \cdot A^{\gamma} \cdot (1-\alpha) \cdot D \cdot (Y - T(D) - k_H H_{ask})^{-\alpha} < 0 \tag{A.3}$$

Eq. (A.3) implies that utility increases with the decrease of travel costs and falls if they grow. It is logical since there is less money available for either a composite good consumption or an improvement in living conditions (i.e. richer amenities or bigger sq. footage of a house and land lot). The impact on housing prices is expected to be mixed: the more distant parcels become less affordable, while price for housing closer to CBD increases since demand for these properties grows.

RHEA was run for two additional scenarios: with travel costs twice lower and twice higher. As expected, utility becomes lower in the case of increased travel costs, and higher in the case of lower travel costs both in Exp1 and Exp5 (Table A.2). The overall effect on prices is mixed in Exp1. In Exp5 total property value in the town grows most likely because higher-income households outbid others for the most central locations driving prices up. The effect is amplified by adaptive price expectations, which include this trend in further setting of ask prices.

A.3. Sensitivity to the deviation of bid prices from ask prices (h)

Variable *h* in Eqs. (6) and (7) determines the upper boundary of the deviation of a submitted bid price from a stated ask price, i.e. how dispersed will bid prices be. The sign of the derivative is straightforward:

$$\frac{\partial H_{bid}}{\partial h} = \begin{cases} 1, & \text{if } h > 0 \\ -1 & \text{if } h < 0 \end{cases} \tag{A.4}$$

Since *h* is a random number between 0% and 10% of the ask price of a seller, the fact whether resulting bid price increases or decreases with a change of *h* on one unit actually depends on a random seed. The question is whether other market mechanisms, such as competition and price update eventually drive price down or up. The simulation results presented in this paper use $h = 0.05$. We run additional scenarios with $h = 0.03$ and $h = 0.1$ (Table A.3).

In case of Exp1 where agents are homogeneous and there are no adaptive price expectations occurring, there is hardly a difference in the resulting transaction prices and total value of all residential properties in the town, confirming the mixed effects anticipated from Eq. (A.4). However, as soon as there are agents with higher budgets and realtors adapt price expectations based on the recent demand and supply, there is a significant growth in prices as bid prices start to be more dispersed (Table A.3). There are two processes contributing to this growth. Firstly, as incomes are heterogeneous there exist high-income buyers who are able to afford a bid price up to 10% higher than an ask price of a seller, which may simply not be affordable in case of homogenous incomes. It results in more successful transaction with bid prices up to 10% higher that ask prices. Secondly, as realtors update their price expectations, they do account for these growing prices. Thus, overall market dynamics responds to the growing demand, which sellers now also take into account when setting their ask prices. This leads to the amplification of price increase leading up to 66% increase in cases when bid price may deviate up to 10% from the anchor ask price.

A.4. Sensitivity to the distribution of preferences for amenities (γ)

The value of average preferences for environmental amenities $\gamma = 0.5$ is based on another study (Wu and Plantinga, 2003) and assumed to be normally distributed. Yet, the standard deviation of this distribution is not known but is likely to affect macro outcomes, such as utility. Assuming that a is the average of households' preferences γ and g is the standard deviation, we estimate the first derivative of utility on g:

$$\frac{\partial U}{\partial g} = \begin{cases} s^{\alpha} \cdot (Y - T(D) - k_H H_{ask})^{1-\alpha} \cdot \log(A) \cdot A^{av+g} > 0 \\ -s^{\alpha} \cdot (Y - T(D) - k_H H_{ask})^{1-\alpha} \cdot \log(A) \cdot A^{av-g} < 0 \end{cases} \quad (A.5)$$

With a more dispersed distribution of gamma, there will be more polarized society in terms of preferences for amenity. Generally speaking, the impact of distribution of preferences for amenity on utility of *searching* households is likely to be mutually cancelled (A.5). However, the distribution may have an impact on the utility of *eventually settled* households in the city. Specifically, households with higher $+g$ (and lower $-g$), i.e. higher preferences for amenity γ, would always prefer properties with higher amenity levels. The effect is opposite for households with lower $+g$ or higher $-g$. Thus, amenity-lovers would always bid for high-amenity properties. However, whether they are able to compete for and get them or not depends on their budgets. In case of heterogeneous budgets RHEA assigns distributions of budgets and preferences independently, assuming that high-income and low-income people are in general may like or be indifferent to environmental amenities with an equal probability. Thus, whether prices go up or down depend also on the incomes of households bidding for properties with heterogeneous levels of coastal amenities.

The simulation results on the differences in the levels of utility under various scenarios of γ distribution for Exp4 and Exp5 are presented in Table A.4. The more dispersed the distribution of preferences among households who eventually settled in the town, the higher the utility. It occurs because differences in the levels of amenities start to matter more: the same attribute (A, coastal amenity) contributes more to a household's utility and households with more polarized preferences can find a better match among heterogeneous properties on a market. Moreover, there is market sorting happening. Specifically, households that like amenities and can afford them, buy coastal properties. Households who value them less, prefer properties with fewer amenities and either settle with cheaper houses gaining more utility from a composite good or go for larger housing without amenities.

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