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Capitalization of Flood Insurance and Risk Perceptions in Housing Prices: An Empirical Agent-Based Model Approach

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Federally regulated or insured lenders in the United States are mandated to require flood insurance on properties that are located in areas at high risk of flooding. Despite the existence of this mandatory flood insurance requirement, take-up rates for flood insurance have been low, and the federal government's exposure to uninsured property losses from flooding remains substantial. Meanwhile, the value of capital at risk varies significantly with flood events and changing risk perceptions, which necessitates mechanisms that stabilize these dynamics. In this article we discuss how a scenario of complete insurance uptake, under various risk attitudes, affects the value of properties in the 100-year and 500-year flood zones. Our results indicate that an increase in flood insurance uptake may provide such a mechanism by lowering the value of capital at risk in the flood zone consistently, independent of homeowners' risk attitudes. We apply an empirical adaptive agent-based model to examine the capitalization of insurance costs, risk premiums, and their interaction in housing prices. Our approach combines widely-used empirical hedonic analysis with the computational economic framework. We highlight the usefulness of our method in capturing the marginal implicit price of homeowners' preferences that may change over time and separately assess the effect of various factors and policies on property values, illustrating the agent-based modeling as a valuable complement to traditional hedonic analysis.

JEL Classification: C53, G22, Q54, R21

1. Introduction

Flooding is the most frequent and costly natural disaster in the world. In the United States, the National Flood Insurance Program (NFIP) aims to redistribute risks and provide immediate relief funds to meet the escalating costs of floods. The success of the NFIP may depend on appropriate pricing and making the flood insurance widely available to homeowners at risk. Certain property owners in Special Flood Hazard Areas (SFHAs) in the communities that participate in the NFIP are required to purchase and retain flood insurance for the duration of their mortgage loans. Yet, despite the existence of this mandatory purchase requirement, take-up rates for flood insurance have been low (Browne and Hoyt 2000; Kriesel and Landry 2004; Michel-Kerjan and Kousky 2010), reaching only 49% of single-family homes in the designated zones nationwide (Dixon et al. 2006). A concern on the low take-up rates has been often expressed following major flood events.

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The full insurance take-up is desirable not only because it creates a safety net but also provides immediate financial funds essential for a recovery process. It is also argued that insurance may lead to a lower capital at stake due to a decrease in property prices (Frame 1998) and communicate risks to home-owners (Nyce et al. 2015). With complete information about flood risks and rational behaviors, risk-based housing price differentials should persist as long as risk differential exists. However, empirical evidence suggests the flood risk discount may diminish overtime. Atreya, Ferreira, and Kriesel (2013) find that house prices fell sharply after a 100-year flood event and the discount disappeared after four years following the flood. Bin and Landry (2013) find a significant housing price discount following Hurricanes Fran and Floyd that declined steadily to the baseline over five to six years. This dependence of housing price differentials on the timing after a flood has confounded the assessments of willingness to accept for flood risks and consequently muddled further analyses of flood risk management options. It is an open question as to how flood insurance, individual risk attitudes of potential homeowners, and the resulting property prices (which form the basis for direct flood damage assessments) interact.

This article aims to quantitatively explore how the full uptake of flood insurance and households' risk attitudes affect property prices in flood zones. In the pursuit of this goal, we pose two research questions: (i) How does the housing market endogenously change with an introduction of a hypothetical full insurance uptake policy that affects households' budget constraints? (ii) How do risk attitudes of individual homeowners affect capitalized flood risks, in the absence or presence of the full insurance uptake policy? Specifically, we assess whether the flood insurance influences housing values, whether this effect differs across flood zones and among behavioral models, and how it capitalizes in housing prices after the introduction of compulsory insurance for all flood-prone properties.

To address this challenge, we employ a novel combination of the traditional hedonic analysis (HA) and an agent-based computational economic model (ACE). Hedonic analysis is a common method to study how various attributes of a composite good contribute to its value (Rosen 1974). It has been actively applied to residential housing markets and often to elicit the impact of flood risks on property values (Macdonald, Murdoch, and White 1987; Bin and Polasky 2004; Kousky 2010; Atreya and Czajkowski 2016). In general, HA utilizes recorded transaction prices that represent the net results of bargaining between buyers and sellers (Bockstael 1996). However, the implicit price estimates based on past transactions may not be robust when underlying individual behaviors or market conditions change, altering traders' willingness-to-pay and willingness-to-accept. ACE approaches to modeling property markets represent a flexible alternative (Nolan et al. 2009; Parker 2014). This simulation method models economic systems with heterogeneous agents that act, interact, and learn according to defined rules (Farmer and Foley 2009). ACE markets are usually based on decentralized bilateral trading among agents (Tesfatsion and Judd 2006; Tesfatsion 2017). In other words, quantities and the prices at which goods are exchanged on market are defined not by an intersection of aggregated market demand and supply curves, but through price negotiations between a pair of agents—a buyer and a seller. Due to this flexible model structure, ACE models provide a platform for wider exploration of out-of-equilibrium dynamics (Arthur 1999), agent heterogeneity (Kirman 1992), bounded rationality (Simon 1997), and interactions and learning between agents (Axtell 2005). The major strength of using an ACE model in our study is that we can systematically run scenarios with various behavioral assumptions, such as individual risk tolerance, as well as insurance or its absence, to create a large data set of simulated transactions suitable for traditional hedonic analysis. By analyzing this pool of data, we are able to discern the effects of different factors—insurance, risk attitudes, or their interactions—and to quantitatively assess their marginal contribution to the flood risk discounts capitalized in housing prices.

The strengths and limitations of agent-based computational economic models have been well documented (Irwin 2010; Meen 2016). Our agent-based model, integrated with HA, combines the

strengths of two methodologies. We use ACE to trace changes in the aggregated housing market dynamics endogenously as flood insurance costs affect buyers' budget constraints, where both budget constraints and buyers' risk attitudes alter the willingness-to-pay for properties in a floodplain. Also, HA provides an empirical ground to elicit buyers' preferences for housing attributes and serves as a vehicle to model adaptive price expectations. When ACE and HA are combined, a bilateral housing market allows for the exploration of the shift between simulated hedonic equilibria while directly tracing the dynamics of implicit prices of flood risk given different behavioral risk models and assumptions about the flood insurance.

The next section describes the study area and data, briefly discussing information on the NFIP relevant to the understanding of the flood insurance requirement. The details of the method are presented in section 3. In section 4 we discuss the cases in which the flood insurance requirement may be associated with lower property values in flood-prone areas and how risk attitudes of homebuyers may offset the overall reduction. An understanding of these mechanisms may help insurance practitioners and policy-makers make informed decisions on managing flood risks and improving resilience. We conclude with a discussion of our findings and opportunities for future work.

2. Study Area and Data

The NFIP was created in 1968 as a result of the passage of the National Flood Insurance Act, which enabled property owners in participating communities to purchase insurance as a protection against flood losses in exchange for local floodplain management regulations. In 1973, concerns about the costs of flooding and low take-up rates led the United States Congress to make the purchase of flood insurance mandatory for property owners in 100-year floodplains with a mortgage from federally-backed lenders. Still, concern is often expressed following major flood events that many at-risk homeowners remain without coverage. An estimate of take-up rates in 100-year floodplains by RAND Corporation finds high regional variation, with the South and West having the highest take-up rates of around 60%, while in the Midwest, take-up rates are only around 20–30% (Dixon et al. 2006). As of August 2016, about 5.1 million policies were in force nationwide (CBO 2017). The significant NFIP debt mainly associated with Hurricanes Katrina in 2005 and Sandy in 2012 generated broad interest in reforming aspects of the program including implementing a gradual rate increase for higher-risk areas and the mandatory disclosure of flood risk. The flooding from Hurricane Matthew in 2016 and Hurricanes Harvey, Irma, Maria, and Nate in 2017 have further complicated matters by adding over $10 billion to the program's $25 billion debt.

Our study area encompasses the town of Beaufort in Carteret County, North Carolina (Figure 1). The area is generally low-lying and prone to flooding. Carteret County is composed of mainland and coastal barrier islands. We exclude the barrier islands of Carteret County, which are exposed to more diverse risk factors, such as hurricane force winds, nor'easters, storm surge, and coastal beach erosion. For the model initialization, we employ spatially referenced data from multiple GIS data sets on the locations of residential housing, environmental amenities and neighborhood quality, flood zone designations, and data on structural characteristics of properties including age, structure square footage, lot size, and number of bedrooms (Table A1). We focus on the single-family residential transactions between 2001 and 2004, where sales prices are inflation-adjusted using a Consumer Price Index to report figures in September 2004 dollars. This hedonic analysis is used to calibrate the pricing of housing at initialization of the integrated HA-ACE model.
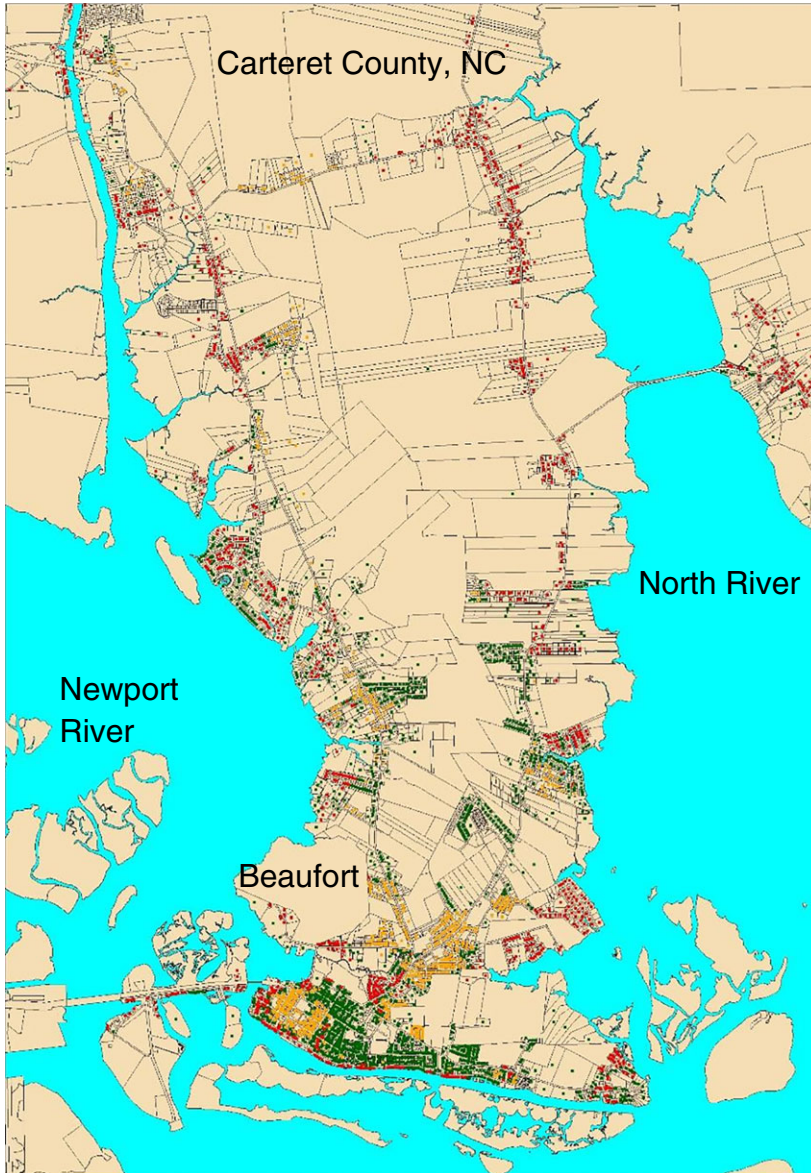
Figure 1. Map of the Study Area.
Notes: Dots indicate the centroid of a parcel with colors indicating the parcels' flood zone designations:
red = 100-year, orange = 500-year and green = safe zone. [Color figure can be viewed at wileyonlinelibrary.com]

The digital flood maps obtained from the North Carolina Floodplain Mapping Program are used to identify properties within flood zones. Flood zone maps provide the location and extent of floodplains in the county. We denote two major categories based on the recurrence interval: a 100-year floodplain, where flood insurance is mandatory for homeowners who finance their purchase through federally regulated lenders, and a 500-year floodplain. The study area in our GIS data set contains 7106 parcels, 3481 of which are used in the analysis. Among the residential properties, 48% are located outside the flood zone, and 30% and 22% are in 100-year and 500-year floodplains, respectively.

Amenities such as the proximity to coastal water (i.e., ocean, sound, and Intracoastal waterways), water frontage, and boat access are highly valued in the coastal housing market. In addition, other locational characteristics such as distance to the nearest central business district (downtown Morehead City), the nearest highway, urban amenities, and quality of schools and recreational opportunities may affect housing prices. Given the spatial correlation/multicollinearity among these spatial attributes, we assume that neighborhood quality is represented by the residuals of the hedonic regression. We apply spatial interpolation (kriging) to quantify the impact of neighborhood quality on property prices (de Koning, Filatova, and Bin 2017). To endow agents with heterogeneous incomes and housing budgets based on the empirical data (Statista 2016; United States Census Bureau 2016; Quigley and Raphael 2004), the results of an ANOVA of the main housing attributes are used as proxies for household's preferences for the corresponding attributes as described in the next section.

3. Methods

To examine capitalization of insurance premiums in housing prices, we apply a spatial ACE model combined with hedonics analysis. We build upon other agent-based models of property markets (Parker and Filatova 2008; Gilbert et al. 2009; Ettema 2011; Magliocca et al. 2012; Magliocca, McConnell, and Walls 2015). Our approach makes a step forward toward the empirical modeling of ACE by running a policy scenario based on HA, GIS data, and distribution of households' preferences and incomes, and the explicit treatment of different behavioral models at the agent level. The core of our model is a simulated bilateral market (Figure 2) where heterogeneous household agents (buyers and sellers) exchange heterogeneous spatial goods (houses) (Filatova 2015).

The ACE model is coded using the R statistical language, and is complemented by HA to examine the effects of the flood insurance take-up on housing prices. The initial model is set up by uploading the entire GIS map of actual properties and their attributes. At the start of the simulation, the expected sales prices for properties are assigned using HA of the actual sales data combined with spatial interpolation (kriging) of the residuals (de Koning, Filatova, and Bin 2017). The model dynamics are realized through a sequence of steps: (i) households who own a property may decide to put it on a market, (ii) real estate agents advise sellers on their asking price given the current market trends, (iii) buyers search for a property that gives them the highest utility under the budget constraint and place a bid, (iv) sellers engage in price negotiations with the buyers who place the highest bid, and (v) real estate agents update their price prediction based on the recent realized bilateral transactions. In this article, we further extend our experiments by altering buyers' budget constraints through insurance premiums for housing in flood zones and individual risk perception. The logic behind buyers and sellers' decisions is discussed below.

There are four scenarios considered in this study: no enforced insurance requirement and the full take-up of flood insurance,[1] tested under two behavioral risk models. Namely, we compare the aggregated market outcomes assuming that individual households are expected utility maximizers with risk-neutral behaviors versus when they completely neglect flood risk when purchasing a house. We perform 50 Monte Carlo runs for each scenario while running the empirical agent-based housing market model for 100 periods, assuming that each period equals six months.

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[1] We assume the full penetration of flood insurance from the start. ACE can also be instrumental in exploring a process of the insurance take-up (Haer et al. 2017; Dubbelboer et al. 2017).
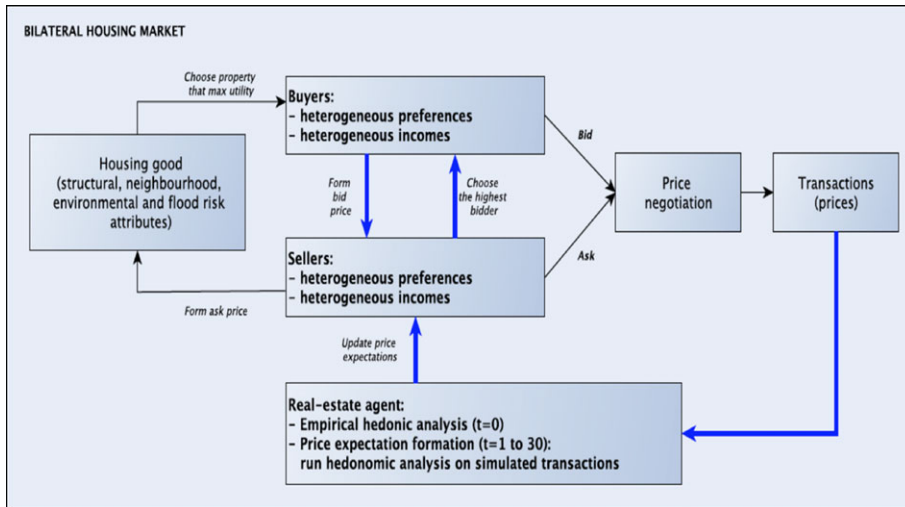
Figure 2. Agent-Based Housing Market Model. [Color figure can be viewed at wileyonlinelibrary.com]

Buyer's Behavior: Risk Avoidance and Flood Insurance

The HA-ACE simulation model is initialized with thousands of heterogeneous household agents differentiated by budgets, as well as housing and location preferences, who search for a house to buy. Each period, 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}, Eqn. 1) for a house in a safe area is parameterized using weights (A_i) that reflect the relative importance of each characteristic ($X_{i,norm}$):

$$U_{0L} = A_i * X_{i,norm} \tag{1}$$

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[2] that drive the variation in sales prices.[3] Table 1 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 1 serves as a benchmark for the buyers' preferences. The sum of all A_{ij} equals 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.[4]

When choosing a location within designated flood zones, a household operates under the conditions of uncertainty and may experience flood damage. Kousky and Michel-Kerjan (2015)

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[2] We used data from Bin and Landry (2013) that includes 9793 residential property sales between 1992 and 2002.

[3] 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.

[4] 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.

Table 1. 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
Neighborhood quality	35.8	0.10	95

estimate the average flood insurance claim after a flood as approximately 25% of the property value. This serves as a proxy for the extent of actual damages an average household may experience during a flood. We model the disutility of losses as:

$$U_L \begin{cases} = 0.25*U_{0L} & \text{without insurance} \\ = 0.10*(0.25*U_{0L}) & \text{with insurance} \end{cases} \tag{2}$$

with U_{0L} representing the utility of the property in the absence of flooding (Eqn. 1). The disutility of losses in case of insurance is 10% of that without insurance, because we account for losses that are covered by the insurance. This takes into account the disutility of losses that cannot be covered, such as the emotional distress of being displaced along with the loss of personal or family items with sentimental value that goes beyond the financial losses. The total expected damage is a function of expected losses in case of a flood and the probability of a flood occurring. The actual probability of a certain number of floods (N) experienced by a household in 100-year and 500-year flood zones depends on the length of residence (YR). Following de Koning, Filatova, and Bin (2017), the probability of N floods (P_N) is estimated as:

$$P_N = pN*(1-p)^{YR-N}*\left(\frac{YR}{N}\right), \tag{3}$$

where p is the annual probability of a flood occurring, reflected by the 100-year and 500-year flood zone. Consequently, the expected utility (*EU*) a household receives from owning a property equals:

$$EU = \sum_{N=0} U_N \, losses * P_N \tag{4}$$

$$\text{given that} \quad U_{N \, losses} = U_{0L} - U_L * N \tag{5}$$

where $U_{N \, losses}$ is the utility gain for a property considering a specific number of floods. Equation 4 is based on a simple additive Von Neumann and Morgenstern utility function (Pollak 1967). Note that the shape of our utility function is linear with losses (Eqn. 2), implying that buyers in our model are risk-neutral.[5] We acknowledge that this assumption is a simplified one and ignores risk-averse behavior under a concave utility function. However, parameterizing the utility functions for the composite good on empirical data has already been a challenge, especially because we model

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[5] In the first version of the model (Filatova 2015) we used the traditional Cobb–Douglas utility function, therefore assuming that this function is concave and agents are risk-averse. While it is a useful assumption for theoretical modeling, bringing the agent-level decisions toward a more empirical basis required significant adjustments to the utility function (de Koning, Filatova, and Bin 2017).

heterogeneous preferences among buyers.[6] The degree of concavity or convexity of the utility functions would add substantial complexity and require more empirical data to parameterize. Given that validation of agent-based models is challenging enough in and of itself (Windrum et al. 2007), we proceed with limiting the degree of complexity by assuming risk-neutral agents.

While expected utility is a predominant behavioral model to study the decisions under uncertainty, empirical evidence suggests that the households' decisions to buy a property could be made independent of risk. A number of surveys indicate that despite the fact that people realize they live in a flood zone and perceive flood risks as real, this awareness does not affect their choices when buying a house (Burningham et al. 2008; Willis et al. 2011). Others suggest that people residing in flood-prone areas may just have biased risk perceptions. These individuals either do not realize that they bought a property in a flood zone (Chivers and Flores 2002) or they underestimate the objective flood probabilities (Ludy and Kondolf 2012). These subjective risk perceptions may change after a flood, increasing the housing price differentials at least immediately following the flood (Atreya, Ferreira, and Kriesel 2013; Bin and Landry 2013). The question is how these perceptions of risks among individual households interact with the purchase of flood insurance. In order to address this question, we employ two extreme behavioral models: an expected utility model, which assumes that people perceive risks objectively always (Eqn. 4), and a risk-neglect model with complete ignorance of flood risks, which assumes that households enjoy the utility of their properties as if there is no hazard involved (Eqn. 1).

After a buyer has found the property that gives her maximum utility, she submits her bid price to a seller. Buyers' bid prices are anchored to sellers' ask prices varying within a range of ±5% of an ask price of a property of interest. Price negotiations (Figure 2) are modeled explicitly as an auction (Filatova 2015). Buyers that are unsuccessful in securing a property will participate in a market in the next period. Buyers that are not able to find a property within their budget will leave the market.

Sellers and Adaptive Price Expectations

Each period, a random number of properties go for sale. At the beginning of a trading period, sellers announce their ask prices. Price expectation formation is a core process in any agent-based market. While ACE has made major progress in modeling markets of homogeneous goods (Tesfatsion and Judd 2006), it remains challenging to model adaptive prices in property markets. The common ACE approaches to modeling price expectations in the bilateral trading environment do not fit housing markets well: spatial goods are highly heterogeneous and traders have little opportunities to learn efficient prices for such an infrequently purchased good such as housing. The same house in a different location may have a disproportionately different price, as do two houses with different structural characteristics in the same neighborhood. Thus, modeling price expectations in housing markets rely on a mediator who regularly participates in transactions and learns what the appropriate price for any unique house may be. We introduce a real estate agent who observes successful transactions and reestimates hedonic coefficients, allowing for the capture of price changes due to shifting market conditions for different locations. In other words, the outcomes of the bilateral ACE market are registered in a database, which real estate agents analyze to

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[6] We ran a hedonic analysis on data from Bin and Landry (2013) that includes 9793 residential property sales between 1992 and 2002 to elicit preferences of individuals for different attributes.

understand the price trends on a market, as realtors do in reality with Multiple Listing Service[7] data. In the model, a real estate agent uses the simulated transactions of the past six months to estimate a new hedonic function at each period. The new coefficients of this cross-sectional analysis are recorded into the realtor's memory and are used to predict prices in the next periods accounting for both the heterogeneity of spatial goods and the market dynamics.

In summary, each seller forms an ask price for his unique property based on the implicit prices for various structural and neighborhood characteristics of his house, which come from the latest HA run by realtors. This ask price is also adjusted for the relative market power of traders when the real estate agent observes an excess demand for a particular segment of a market. A market segment is defined by properties that have similar characteristics and that are within a certain distance radius of each other. After all buyers make their choices, sellers select the highest bid price, if any, to engage in price negotiations (Figure 2). Unsuccessful sellers decrease their ask prices in the future. Thus, the emerging shifts in housing prices are endogenously driven by the interactions of heterogeneous adaptive buyers and sellers. Due to the differences in households' incomes and preferences for neighborhood amenities across agents, some properties are in higher demand than others. Thus, sellers of those properties will receive more bids, out of which they choose the highest, driving prices up. At the same time, sellers with less or no bids are in the position to accept lower bids. Therefore, an allocation of heterogeneous spatial goods among households with heterogeneous incomes and preferences occurs endogenously via the market sorting. Note that both demand and supply of residential properties are disaggregated in our HA-ACE model. It implies that if agents' preferences or their housing budgets change—due to flood insurance premiums that make it more costly to live in a flood-prone area, for example—it influences individual demand for locations. Cumulatively, this leads to endogenous changes in the aggregate market demand, and to the capitalization of these changes in property prices.

4. Results

To quantitatively explore how insurance and households' risk attitudes affect flood-prone housing markets, we ran four experiments: (i) expected utility model without insurance, (ii) expected utility model with insurance, (iii) risk-neglect model without insurance, and (iv) risk-neglect model with insurance. We ran HA on simulated sales in each of the four experiments. Traditionally, HA is done only on one set of transactions over a certain time period. The discount for properties located in the flood zone is given by the coefficient of the 100-year and 500-year flood zone dummies in the HA. We perform multiple Monte Carlo runs of our four experiments, and consequently run the HA of the simulated transactions multiple times to come up with an average discount for properties located in the flood zone. We estimate the coefficients of the 100-year and 500-year flood zone dummies on the basis of ACE model sales in the last five years of the simulations.[8] The four experiments, each performed 50 times, deliver 200 hedonic regression results, providing us with a set of 200 flood dummy regression coefficients that differ among the four experiments. We compare the

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[7] http://www.mls.com/.

[8] We limit our analysis to the last five years of the simulations to focus on the period when the agent-based housing market has converged to an equilibrium. ACE models are inheritably dynamic models, which may or may not converge to an equilibrium or a set of equilibria. Our agent-based housing market model does converge to an equilibrium, meaning that the market price stabilizes.

Table 2. Summary Stats for the Flood Zone Coefficient

Flood Zone	Average Price Compared to Safe Zone	Discount for Flood Insurance	Discount for Flood Risk	Flood Risk * Insurance
100-year	−23.0% (±0.7%)	−8.1% (±1.0%)	−6.2% (±1.0%)	+5.2% (±1.5%)
500-year	−20.2% (±0.6%)	−4.4% (±0.8%)	0	0

average flood dummy coefficients by running an ANOVA on these coefficients (dependent variable), with the experimental settings and their interaction (risk attitude, insurance policy, risk attitude with insurance policy) as independent variables.

To assess how risk attitudes and insurance premiums capitalize into property prices separately, we compare the four experiments within the ANOVA. None of the coefficients are measured based on their absolute value for the following reason: we find a baseline price discount for properties located in the flood zones that cannot be attributed to either capitalized insurance rates or capitalized risk attitudes. We assume that a discount for properties in the flood zone reflects people's perception of risk and the capitalization of flood insurance. Yet, when risk perceptions and flood insurance equal zero, we still find a discount for properties in the flood zone in our simulation experiments (Table 2, column 2) where there should be none. This discount reflects the mean coefficient of the flood zone dummy in the experiments with risk-neglecting buyers and without the full insurance uptake. In fact, the second column in Table 2 is derived from the intercept in our ANOVA, where both factors (risk attitude and insurance) are equal to zero (Appendix B outlines how the percentages in Table 2 are calculated). In our ANOVA, we compare the differences in the coefficients of the flood zone dummy among the experiments, while the coefficients in all experiments deviate from zero statistically significantly - and hence the intercept is significantly different from zero. The value of the intercept is −0.261 and −0.226 in the 100-year and 500-year flood zones, respectively. We consider this as the baseline price discount for properties located in the flood zone compared to properties outside the flood zone. This discount distorts our estimates of the flood dummy coefficient in the simulations, and is likely governed by spatial correlation between location in the flood zone and other housing attributes. This is further explained in detail in de Koning, Filatova, and Bin (2017).

We discuss the results of the integrated HA-ABM model in line with two issues. Firstly, we identify the pure capitalization of flood insurance premiums in housing prices under the hypothetical scenario of the full insurance take-up. Secondly, we compare the effect of flood insurance with the effect that the risk-neglect behavior may have on housing values. Our agent-based model offers a virtual lab in which we experiment with insurance premiums and households' risk attitudes. The combination with the hedonic pricing method allows us to separately identify the marginal contribution of risk attitudes and flood insurance to the prices of properties in the flood zone. Moreover, we show other relevant variables in a housing market that our agent-based model enables us to analyze on top of the hedonic price analysis. The results are discussed step-by-step below.

Discount on Property Prices in the Flood Zone Due to Insurance

First, we look at the flood dummy coefficients based on HA of simulated transaction prices with and without insurance. We compare the means of the coefficients to estimate how much the property values in the flood zones would decrease because of the flood insurance premium with the full insurance uptake. In the simulations, buyers take the insurance costs into account in their housing budget, and it subsequently reduces the amount that buyers spend on housing. This is not the

case in the simulations where the insurance is absent. Thus, the comparison between the coefficients of these scenarios highlights the marginal implicit price of insurance costs, which add to buyers' budget constraints and capitalize into the housing price in the flood zone.

Column 3 in Table 2 shows how flood insurance capitalizes into property values in the 100-year and 500-year flood zones. In the case of full insurance uptake, we see that the average price of a property is reduced by −8.1% (±1.0%) and − 4.4% (±0.8%) on average in the 100-year and 500-year floodplains, respectively, irrespectively of how individuals perceive risks. In other words, the coefficient of the flood zone dummy is on average reduced by 0.085 (±0.010) and 0.045 (±0.008) in the 100-year and 500-year flood zone, respectively as a result of insurance premiums that capitalize into property values. Equations—in Appendix B explain more in-depth how the difference in the coefficients of the flood zone dummy between the simulations are used to calculate a percentage discount for a property in the flood zone driven by the insurance costs.

In addition, we also explore parameters in the model that explain the discount for properties with the full insurance take-up. As described before, insurance premiums add to the costs of flood-prone properties affecting the budget constraint of buyers. It makes properties in the flood zone less affordable. That is, a property in the flood zone, which gives the highest utility for a certain buyer, will likely be close to the maximum budget for that buyer. Thus, this property may become unaffordable when insurance costs are included. At the same time, higher income buyers who could afford that particular property will most likely avoid it because it does not maximize their utility: for the same housing budget, they can afford a better house and avoid additional insurance costs. This leads to a decrease in demand of properties in the flood zone followed by the need for sellers to lower ask prices for properties that require flood insurance. Overtime, these feedback effects make properties in the flood zone more affordable again for the former group of buyers since they would have to spend less of their budget on the housing. Indeed, looking at the relative amount that buyers spend on a house, we see that buyers of properties in the 100-year flood zone spend on average 88.4% of their maximum housing budget[9] on a house when they do not need a flood insurance, while they spend on average 83.7% of their housing budget when required to purchase a flood insurance. Thus, buyers in the 100-year flood zone spend on average 4.6% less on housing when they need to incur additional cost on flood insurance. In the 500-year flood zone, buyers save 3.1% of their budget on housing under the full insurance take-up scenario.

Separating the Effect of Risk Attitudes from the Effect of Flood Insurance

Next, we compare the expected utility model with the risk-neglect model. It allows us to calculate how risk attitudes capitalize into property prices and to quantitatively examine an interplay between imperfect information about risks among households and the flood insurance. The factor "risk attitude" in the ANOVA (Table 2, column 4) shows the discount for properties in the flood zone that can be attributed to the capitalization of risk attitudes among the buyers. The expected utility model differs from the risk-neglect model in that buyers perceive flood risk and take it into account when searching for a property that maximizes their utility under budget constraints. Buyers in the risk-neglect model do not consider the flood zone status of a property in their utility calculations, while buyers in the expected utility model reduce their utility by the objective probability of

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[9] The maximum housing budget is the maximum amount that buyers can afford to spend on housing. In most cases they end up spending less than this amount. In the simulations they spend on average about 88–89% of this amount, but it varies depending on whether insurance premiums are also considered by buyers.

flooding, multiplied by expected damages. These perceived losses in utility decrease the demand of informed buyers for properties in the flood zone under the expected utility model, leading to a reduction of property prices therein. Hence, the mean coefficient of the flood zone dummy is lower in the expected utility model than in the risk-neglect model. Table 2 (column 4) shows that the expected utility model lowers the value of 100-year flood zone properties by −6.2% (±1.0%) compared to a housing market where buyers ignore flood risks. In other words, when buyers perceive risks objectively, the price of properties in the flood zone is reduced by −6.2% on top of the discount for flood insurance premiums. These results show that prices for properties in the flood zone depend on how buyers value the risk of living in the flood zone. When buyers neglect flood risks in a market, the aggregate flood risk discount is less than it would be in markets with traders who are perfectly informed and have neutral risk attitudes. Generally, a higher risk perception leads to a larger discount for properties located in the flood zone. We can use the simulations in our ABM to quantify the marginal implicit price of flood risk in the market (de Koning, Filatova, and Bin 2017). Risk attitude had no significant effect on property values in the 500-year flood zone, likely because the probability of flooding is too small to have a relevant impact on the price.

Again, we look at various other measures in the model to see how the discount for properties in the flood zone due to risk manifests itself in the housing market. Figure 3 shows how property sales in the 100-year and 500-year flood zone and outside the flood zone are distributed among income groups in the expected utility model and risk-neglect model. It appears that the 100-year flood zone is relatively highly represented by the 20% of homeowners with lowest income, while properties outside the flood zone are relatively highly represented by the 30% of households with highest income. Hence, the discount for properties in the 100-year flood zone results in a larger number of low-income households that occupy these properties. Comparing the expected utility model with the risk-neglect model, we also find that there are slightly more high income households (highest 10% in particular) in the 100-year flood zone when people ignore the risks. In the expected utility model, we see slightly more low income (lowest 40%) households in the 100-year flood zone. This pattern is initially driven by the reduction of property prices resulting from lowered demand given buyers' risk attitudes. Furthermore, due to the market sorting, lower income households are allocated to the areas where property prices are lower, leading to the path dependence.

In addition to the individual effect of the two main factors (risk attitude and insurance) in the ANOVA on the coefficients for the 100-year and 500-year flood zone dummies, we also find a significant interaction effect in the 100-year flood zone. Full insurance take-up in combination with the expected utility model increases the mean price of a property in the 100-year flood zone by +5.2% (±1.5%) (Table 2, column 5), leading to the overall discount of −9.3% for flood zone properties. While insurance premiums and flood risk both capitalize into property prices leading to a discount for properties in the 100-year flood zone (reducing the value of a property by −8.1 and −6.2%, respectively), we also see that expected damages are lower in the expected utility model with insurance than in the expected utility model without insurance (Table 3). Hence, the discount for properties in the flood zone in the simulations with expected utility traders and the full insurance

Table 3. Average Discount for a Property in the 100-year Flood Zone in the Four Experiments, Using Risk Neglect without Insurance as Baseline

Experiment Settings		Insurance	
		False (%)	True (%)
Risk attitude	Risk neglect	0	−8.1
	Expected utility	−6.2	−9.3

Figure 3. Properties Sold in Each Flood Zone, Distributed in Household Income Percentiles. [Color figure can be viewed at wileyonlinelibrary.com]

uptake is less than the sum of the effects. Flood insurance comes with additional costs for an individual homeowner in the form of annual premiums, as well as with additional benefits in the form of damage coverages in the case of a flood. The fact that insurance coverages compensate (part of) the damage alters buyers' utility, which capitalizes positively into prices for properties in the 100-year flood zone. Thus, despite the fact that maximizing the expected utility among traders results in an additional discount for properties in a flood zone, we find that this discount reduces with the full insurance take-up, as anticipated in theory (Frame 1998).

Figure 4 shows the mean coefficients (± one standard deviation) of the 100-year flood zone dummy (A) and 500-year flood zone dummy (B) of the four simulations. It illustrates that flood insurance consistently causes a lower price for properties in both the 500-year and 100-year flood zone, independent of buyers' risk attitudes. Empirical work finds that price discount changes overtime as individual risk perception of market participants is magnified after a flood event (Atreya, Ferreira, and Kriesel 2013; Bin and Landry 2013). Our agent-based model integrated with HA allows us to consider two extremes at the individual household level—fully informed traders with risk-neutral attitudes and individuals who entirely ignore these risks—and to study how market outcomes change in each case. Our analysis indicates that irrespective of whether individuals perceive risks objectively or ignore them completely, a hypothetical scenario of full flood insurance take-up leads to a price decrease in the flood zone. Lower value for the capital at stake emerging in a flood-prone housing market has two positive implications. Firstly, an individual choosing to buy a house in a flood zone is compensated for the additional insurance costs by paying a lower price for the hazard-prone house. Secondly, lower property values in flood zones translate into less direct damages in the case of a flood, leading to less pressure on the NFIP and eventually taxpayers, as well as to less incentive to redevelop in the risky zone (Table 4). Hence, these results may provide important policy implications.

5. Discussions and Conclusions

This article contributes to the existing literature on flood insurance by exploring the effects of a hypothetical policy and by illustrating a methodological value of combining HA with simulations.
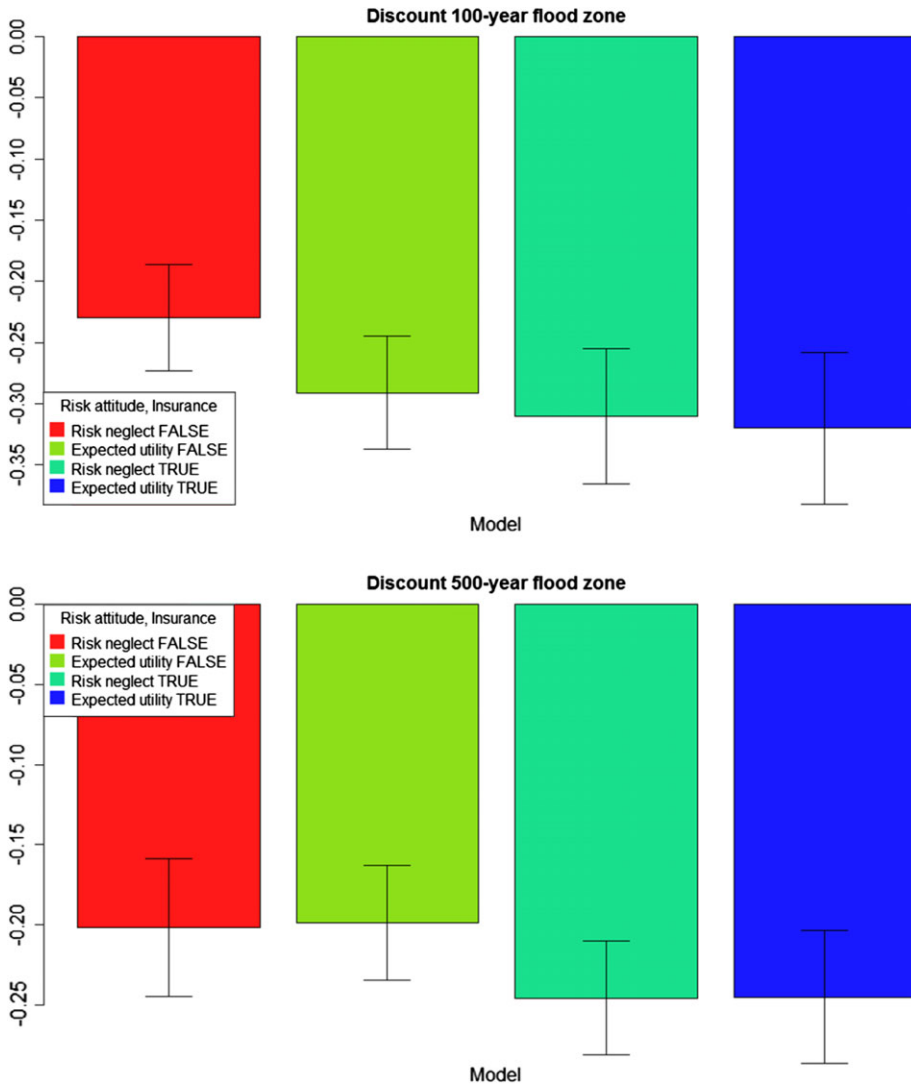
Figure 4. Discount for Properties in the 100-year (A) and 500-year (B) Flood Zone. [Color figure can be viewed at wileyonlinelibrary.com]

Firstly, we assess the impact of flood insurance on property prices under various risk attitudes in a hypothetical scenario of 100% take-up. Secondly, we intend to show the usefulness of ABM as a tool to address such challenges that require disentangling different policy effects in a market. We conclude by critically reflecting on the challenges we still face with this approach and suggest opportunities for future work.

Table 4. Total Housing Capital at Risk in the 100-year Flood Zone

		Insurance	
Experiment Settings		False	True
Risk attitude	Risk neglect	$ 158.4 M	$ 150.5 M
	Expected utility	$ 152.3 M	$ 148.6 M

Policy Impacts: Effect of Insurance and Flood Risk on Property Values

The results from our agent-based model grounded in HA show that insurance reduces the property values on average by −8.1% and −4.4% in the 100-year and 500-year flood zone, respectively. We compare the discount for properties in a flood zone in a scenario with 100% insurance uptake and a scenario without insurance. The effect is consistent independent of households' risk attitudes, implying that the flood zone discount is present even if risk is ignored among buyers. This shows that flood insurance serves as a mechanism to convey risk information to buyers independently of risk attitudes or a potential flood risk information asymmetry, ensuring that the flood risk is capitalized into property values. Our simulation is based on the assumption of full compliance, but in reality some homeowners may still choose not to be covered by the insurance. The net effect should then depend on the enforcement effort and the compliance to the proposed change.

We find that risk attitudes also affect property values in addition to the insurance effect, but its effect on property values is less than the capitalized effect of insurance. When people are risk-neutral, the value of properties in the 100-year flood zone is reduced by another −6.2% on top of the insurance effect. We find no effect of risk attitude in the 500-year flood zone. Given that expected damages in the 500-year flood zone are rather low, it is likely that the effect is too small to yield a significant effect on property prices in the 500-year flood zone.

Furthermore, we find that the insurance reduces the effect of risk perceptions in the expected utility model. Expected damages are reduced because they are (at least partly) covered by the insurance, making people feel less at risk should a flood occur. The damages that are covered by flood insurance capitalize as an increase in property values by +5.2% in the 100-year flood zone in the expected utility model with insurance relative to the case with the complete ignorance of risks, both still delivering a flood zone price discount of −8.1% and −9.3% correspondingly. This minimizes the difference between the expected utility model and risk-neglect model in case of 100% insurance uptake, which has important policy implications. Risk perceptions may be biased depending on information and experience with flooding events (Atreya, Ferreira, and Kriesel 2013; Bin and Landry 2013). Experience drives changes in people's risk attitudes, and hence the discount for properties in the flood zone is not stable overtime. This implies that the value of capital at stake is very dependent on the volatility of homeowners' risk attitudes unless there is a market mechanism in place that stabilizes the value of properties in the flood zone overtime (Bagstad et al. 2007; Filatova 2014). The results in our simulation study suggest that the full insurance uptake may provide such a mechanism for two reasons: (i) the value of insurance premiums capitalizes into property prices, thereby reducing the total value of capital at stake, and (ii) the insurance may reduce people's risk perceptions because (part of) the expected losses are covered by future insurance claims.

Methodological Lessons: Benefits of Agent-Based Computational Modeling and Open Challenges

The issues addressed in this article present several scientific challenges. Namely, (i) quantifying the impact of insurance and risk in hazard-prone dynamic markets (Harrison et al. 2001; Bin, Kruse and Landry 2008), (ii) isolating the marginal impacts of individual housing attributes in a housing market where many of these attributes are spatially correlated, (iii) dealing with risk attitudes that change overtime (Bin and Polasky 2004; Atreya, Ferreira, and Kriesel 2013; Bin and Landry 2013), and (iv) addressing the issue that property values in hazard zones are pushed up by the demand for environmental amenities and people that ignore the risks (Bin, Kruse, and

Landry 2008). The results of our model, which integrates HA and agent-based simulations, illustrate the usefulness of the method in addressing these scientific challenges.

While we try to rely on empirical data and secondary literature sources as much as possible here, the numbers presented in this article should not be taken literally for a policy analysis or for drawing any direct policy implications. This should rather be considered as an illustrative case, which shows the possibilities of the method that combines traditional empirical HA and computational economics simulation models to directly trace market impacts of a policy intervention under adaptive market dynamics. By combining the strengths of two methodologies, we are able to run experiments and quantify the impacts of the complete take-up of flood insurance that alter households' budgets constraints. Although hedonic studies have demonstrated a link between insurance premiums and price discounts, the innovation of our approach lies in its ability to trace the marginal contribution of flood insurance and risk in isolation, as well as in their interaction. We provide an experimental landscape in which we can vary certain parameters while keeping others constant, and vice versa. We can systematically run multiple simulations under the same settings to estimate a mean effect of various factors on property values in the flood zone. In contrast to hedonic studies in real markets that are limited to a single time series of sales, our agent-based housing market model can produce multiple time series under the same set of assumptions. This way, we can eliminate stochastic effects caused by availability of properties on the market and shifting preferences of buyers overtime. We can also work around spatial correlation in housing attributes by comparing outcomes between sets of experiments. Moreover, in scenario studies, we can use our model to explore policy options that could be adopted to inhibit price changes caused by changing risk attitudes. In the hypothetical scenario of the 100% insurance uptake, we explore how this affects the value of capital at stake.

Finally, in our agent-based simulations we can assess other relevant market parameters, such as households' budgets spent on housing and income distributions among different housing sectors, which allows us to go beyond HA and study the impact of certain policies on the market in more detail. Agent-based computational economic models trace the emergence of aggregated market-level features such as market demand or prices and number of sales, as well as provide an opportunity to record relevant disaggregated data such as incomes or preferences of traders. It allows a unique analysis of macro-level phenomena and patterns using micro-level data (Sun et al. 2014; Filatova et al. 2011).

Challenges and Future Work

Several caveats are in order for our analysis. First, our initial HA is based on a township in Carteret County, while the income variable comes from general U.S. public and the preference variable is derived from Pitt County in North Carolina. Albeit spatially close, the simulated demand in our model is not of the same population from the hedonic analysis of Bin, Kruse, and Landry (2008). We do not consider this problematic for the purpose of this research because the results should in any case be interpreted as a representative example, rather than a case-specific study. Yet, it may partially explain why we find such a large discount for properties in the flood zone in the experiment with risk-neglecting buyers without insurance (Table 2, column 2). Namely, the preferences of buyers in our simulations are not exactly in line with the preferences of actual buyers in our housing transactions data set. At initialization, we obtain our data from a market that is structured according to preferences and budgets of one set of buyers, while during our simulation the preferences and budgets of another set of buyers capitalize into property values. Although the

hedonic coefficients update at each time step to match with buyers' preferences, there is a remaining bias in the coefficient estimates that amplifies the discount for properties in the flood zones, which is caused by multicollinearity in housing characteristics (de Koning, Filatova, and Bin 2017). Hence, the hedonic analysis in our agent-based simulations can only be useful when it is applied in a comparison between multiple experimental scenarios.

Second, our model requires disaggregated empirical data on buyer preferences for different housing and location attributes. We tried to disaggregate buyers' preferences by inferring them from transactions in an actual market through the ANOVA since the strength of agent-based modeling lies in simulating the aggregated behavior of a system that emerges from individual choices, preferences, and interaction of individuals (Farmer and Foley 2009; Tesfatsion 2006; Tesfatsion 2017). Hence, one needs data on individual preferences to simulate how macro patterns emerge from the bottom up, rather than attempting to infer preferences of individuals from the emerging system. We strived to move away from theoretical modeling, bringing the agent-level decisions toward a more empirical basis in which we chose to compromise in the complexity of the theoretical models. In an attempt to infer buyers' preferences with empirical data, we simplified the utility function by assuming a linear risk-neutral behavior while the typical shape is concave, representing the risk-averse behavior. In order to properly capture individuals' risk-averse (or risk-seeking) behavior, the degree of concavity or convexity of these utility functions need to be parameterized with empirical data. Given the complexity and the many interactions between individuals that give rise to the behavior of a system, any errors in the modeled behavior may propagate through the system. Intensive Monte Carlo simulations are necessary to assure the reliability of agent-based market estimates. Yet, any errors in the underlying micro data may naturally lead to amplified errors on the macro scale.

Third, our simulation is based on the assumption of the full insurance compliance, but in reality some homeowners still would choose not to be covered by the insurance. The net effect of a program that stimulates insurance uptake should depend on the enforcement effort and the compliance to the proposed change.

This work could be extended in several directions. Firstly, a realistic policy analysis requires more precise data on insurance premiums and coverage as well as disaggregated data of preferences for amenities and housing goods. It may require a survey that explicitly studies risk preferences and perceptions of sellers and buyers, and elicits any behavioral rules underlying their location choices. Secondly, as discussed by Viscusi (1985) and Smith and Desvousges (1988) people constantly learn about risks they face. We simulated two models of individual risk attitudes in a static way. In reality, risk perceptions change overtime as people forget or get reminded about a specific hazard such as flood in our case, which can seriously alter their location choices and willingness-to-pay for safety. Empirical research on housing markets in flood-prone areas captures that there are indeed dynamics in flood risk perceptions that are exacerbated just after a disaster and gradually forgotten, as reflected in price discounts changing dramatically overtime. Our ACE model integrated with traditional hedonic analysis could be used to study how the flood risk capitalization in housing prices changes overtime as people's risk perceptions get updated or vanish, and assess how the insurance could be used to interfere with these dynamics. Thirdly, as such changes in individual behavior could be captured and parameterized with data, one may explore non-marginal effects, which are anticipated in economic systems in climate change world (Stern 2016). As opposed to majority of economic tools that are designed to study gradual changes along the same trend, computational economics models are not bounded to such marginal dynamics. This could potentially open new methodological opportunities and shift research frontiers to quantitatively examine non-marginal changes as well.

Appendix A: Descriptive Statistics of the Data

Table A1. Summary Statistics of the Data (N = 3481) for Beaufort, NC

GIS Parcel Attribute	Average	Std. Dev.	Min	Max
Number of bedrooms	2.7	1.09	0	12
House age	40.2	29.9	0	274
Sq. footage of a house	1676	802.8	160	6080
Lot size in acre	1.03	3.09	0.005	42.39
Whether a house is in 1:100 flood zone	0.30	0.46	0	1
Whether a house is in 1:500 flood zone	0.22	0.41	0	1

Appendix B: Derivation of Property Price Discount

The following equations are meant to clarify how we calculated a percentage discount for properties in the flood zone driven by insurance costs. The same procedure applies to the risk attitude models. Equation B1 shows the hedonic price of a property in the 100-year flood zone in the simulations without insurance (ins = 0). The hedonic coefficient for the 100-year flood zone dummy is given by $a_{fz100,\,ins\,=\,0}$. The hedonic coefficients for all other property characteristics (i) are given by a_i

$$ln\left(price_{fz100,ins=0}\right) = \sum a_i X_i + C + a_{fz100,ins=0}*1 \tag{B1}$$

As we are using the natural log of sales prices in the hedonic analysis, the actual sales price is given by the e exponent of the hedonic coefficients and the property characteristics. Equation B2 shows the price of a property located outside the flood zone.

$$price_{out} = exp(\Sigma\, a_i X_i + C) \tag{B2}$$

The price of a property located in the flood zone can be estimated by calculating the price as if it were outside the flood zone, and multiply it with the e exponent of the coefficient of the 100-year flood zone dummy (Eqn. B3).

$$price_{fz100,\,ins=0} = price_{out}*exp\left(a_{fz100,\,ins=0}\right) \tag{B3}$$

The percentage difference between a property inside and outside the flood zone, all else being equal, is given by Equation B4.

$$\Delta price_{fz100,\,ins=0}\,(\%) = \frac{price_{fz100,\,ins=0} - price_{out}}{price_{out}}*100 \tag{B4}$$

Substituting $\frac{price_{fz100,\,ins=0}}{price_{out}}$ for $exp(a_{fz100,\,ins\,=\,0})$ (Eqns. B3, B4), we get Equation B5, which shows how a percentage discount for a property located in the 100-year flood zone is calculated directly from the coefficient of the 100-year flood zone dummy in the hedonic analysis.

$$\Delta price_{fz100,\,ins=0}\,(\%) = \left(exp\left(a_{fz100,\,ins=0}\right)-1\right)*100 \tag{B5}$$

In a similar way, we can calculate the relative price discount for properties in the 100-year flood zone with and without insurance. We first compare the hedonic coefficients of the 100-year flood zone dummy of the simulations with insurance (ins = 1) with those of the simulations without insurance (ins = 0). The difference is given by $a_{fz100,\,ins}$ in Equation B6.

$$a_{fz100,\,ins=1} = a_{fz100,\,ins=0} + a_{fz100,\,ins} \tag{B6}$$

Similar to Equation B3, we can estimate the price for a property in the 100-year zone with insurance by multiplying its price without insurance, all else being equal, with the e exponent of $a_{fz100,\,ins}$. Thus, $a_{fz100,\,ins\,=\,0}$ can be substituted for $a_{fz100,\,ins}$ in Equation B5 to calculate the percentage discount for a property in the 100-year flood caused by insurance premiums. This can be calculated directly from the difference in the coefficients of the 100-year flood zone dummy $a_{fz100,\,ins}$ between the

simulations with and without insurance. The same equations are applied between the simulations with risk-neglecting buyers and expected utility buyers to calculate a percentage discount for properties in the flood zone driven by changes in risk attitudes.

$$price_{fz100, ins=1} = price_{fz100, ins=0} * exp(a_{fz100, ins}) \tag{B7}$$

The discount for properties in the 100-year flood zone in our simulations, a_{fz100}, depends on the model of risk attitude (RA) and insurance (ins). Both are either 0 or 1, and represent risk neglect or expected utility and false or true, respectively. We apply linear regression on the flood zone coefficients of the simulations (N = 200), with RA, ins and their interaction $ins*RA$ as explanatory variables. Equation B8 shows the variables that are predicted with this linear regression.

$$a_{fz100}(ins, RA) = I + a_{fz100, ins} * ins + a_{fz100, RA} * RA + a_{fz100, ins \times RA} * ins * RA \tag{B8}$$

which includes intercept (I), discount for insurance ($a_{fz100, ins}$), discount for flood risk ($a_{fz100, RA}$) and interaction effect of insurance and flood risk ($a_{fz100, ins \times RA}$). These variables are used in Table 2. The values in Table 2 are constructed by substituting $a_{fz100, ins = 0}$ in Equation B5 for all of the variables I, $a_{fz100, ins}$, $a_{fz100, RA}$ and $a_{fz100, ins \times RA}$ in Equation B8. They represent row 2, columns 5, 2, 3, and 4, respectively.

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