Journal of Environmental Economics and Management 105 (2021) 102397

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem

Hold the line: Modeling private coastal adaptation through shoreline armoring decisions☆

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ARTICLE INFO

Article history:
Received 3 October 2019
Received in revised form 18 August 2020
Accepted 3 November 2020
Available online 9 November 2020

JEL classification:
Q54
Q58
R14
R52

Keywords:
Land use
Climate adaptation
Spatial spillovers
Erosion
Sea-level rise
Armoring

ABSTRACT

A primary conduit for coastal adaptation to climate change on private land is the hardening, or armoring, of the shoreline to mitigate the effects of erosion and sea-level rise (SLR). When such decisions are made at the parcel-level, there is potential for spatial spillovers, including externalities due to deflected wave action and peer effects. We estimate a discrete choice model of landowner armoring choices from 1990 to 2015 in the U.S. state of Oregon that suggests the impacts of spatial spillovers are highly influential determinants in these private adaptation decisions. Our landscape simulations excluding spatial spillovers may under-predict future armoring by 37–97 percent. From scenario-based simulations, we then demonstrate the primacy of policy, as a removal of a current land-use regulation that limits armoring has potential to significantly increase future armoring by 69 percent. Furthermore, inclusion of SLR projections suggests armoring would increase an additional 5.4 percent within four decades.

The inherent tradeoffs between protection of private assets and management of the public good aspects of our coastlines are a source of increasing conflict given threats posed by erosion and sea-level rise (SLR). These risks loom large with potential damages from SLR in the United States (U.S.) predicted to be up to 9.3 percent of GDP by 2100 absent of adaptation (Hinkel et al., 2014) and with displacement of over 13 million people possible due to inundation (Hauer et al., 2016). The severity of

☆ The authors thank the editor and two anonymous reviewers for feedback that improved this manuscript. We thank Meg Reed and the Oregon Department of Land Conservation and Development for access to their Goal 18 database, and Laura Barreiro-Fernandez and Christopher Parrish for their assistance with geospatial data. We thank David Lewis, David Kling, Yong Chen, Junjie Wu, Peter Ruggiero, seminar participants at Boise State University, University of Wisconsin-La Crosse, Western Michigan University, and Oregon State University, and conference participants at the 2019 AERE Summer Conference, the 2019 W-4133 Annual Meeting, the 2018 AAEA Annual Meeting, the 93rd WEAI Annual Conference (2018), and Camp Resources 2018 for helpful comments. We acknowledge funding that supported this research from the NOAA National Centers for Coastal Ocean Science Competitive Research Program through NOAA Cooperative Institutes Program award numbers NA11OAR4320091A and NA16OAR4320152 to the Cooperative Institute for Marine Resources Studies at Oregon State University and Oregon Sea Grant under award no. NA18OAR170072 (CDFA no. 11.417) from NOAA's National Sea Grant College Program, US Department of Commerce, and by appropriations made by the Oregon State Legislature. The authors certify that they have no conflicts of interest associated with the material in this article.

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https://doi.org/10.1016/j.jeem.2020.102397
0095-0696/

these threats have increased calls for decision-relevant science to improve adaptation planning (Moss et al., 2013; Petes et al., 2014) and better the understanding of coastal adaptation decisions (Gopalakrishnan et al., 2018). This paper fills a gap in economists' understanding of how private adaptation incentives and land-use policies may influence the temporal and spatial pattern of investments to mitigate current and future coastal risks.

The decision of a landowner about when and how to adapt to coastal risk is likely influenced by physical factors such as erosion rates, elevation, and the location of homes or other structures relative to ocean wave action. Decisions of neighboring landowners may also influence the adaptation choice. The physical risk faced by a parcel may increase if choices of neighbors offer potential to accelerate the erosion processes, creating a spatial externality. Landowners may also learn from neighboring land-use changes about the effectiveness, costs, and aesthetics related to coastal adaptation, as well as receiving signals about future coastal risks. These peer effects may influence an individual landowner's adaptation decision beyond just physical risk characteristics affecting their own parcel. Here we investigate the relative effects of both physical risks and spatial spillovers on the probability of a coastal property owner making a private adaptation choice to change land use. Our application focuses on coastal Oregon in the U.S. where private oceanfront landowners have the option to harden, or armor, their shoreline if they are eligible to do so under state land-use planning regulations.

Given a limited choice set for private and public coastal adaptation options, understanding the incentives and relevant metrics that lead to adoption of these strategies is key to adapting to climate change. Although recent work suggests much of the expenditure on coastal adaptation in the U.S. by 2100 will be private shoreline armoring (Neumann et al., 2015), prior economic studies focus primarily on public decisions about beach nourishment. This literature has assessed the potential for spatial spillovers (Gopalakrishnan et al., 2017),[1] estimated optimal replenishment cycles (Smith et al., 2009) and identified housing market impacts related to nourishment events (Dundas, 2017; Qui and Gopalakrishnan 2018) and the value of wider beaches (Gopalakrishnan et al., 2011; Landry and Hindsley 2011). Despite uncertainty in the drivers and outcomes of private adaptation decisions, the topic is noted for its importance to efficient coastal management (Landry 2011; Gopalakrishnan et al., 2016). Related coastal armoring studies external to the land use decision further signify the topic importance. A survey of coastal landowners suggests they perceive armoring to be a cost-effective and durable option to combat shoreline erosion and that neighboring shoreline conditions are a strong predictor of current land use (Scyphers et al., 2015). Both the existence of shoreline armoring structures (Jin et al., 2015; Walsh et al., 2019) and the option to install one (Dundas and Lewis 2020) have been recently shown to capitalize into housing values. The presence of spatial discontinuities in property rights related to armoring also has potential to impact housing markets (Dundas and Lewis 2020). Together, this prior evidence suggests that private adaptation decisions are likely to have economic impacts on coastal communities and alter future land-use patterns.

We first present a simple analytical model that suggests the potential for spatial spillovers between neighbors could result in a negative externality due to deflected wave action from an armored shoreline. The presence of negative spatial externalities may lead individuals to invest more in private adaptive measures than socially optimal. This outcome implies a fundamentally different outcome compared to public provision of coastal protection services (e.g., beach nourishment). To test our framework empirically, we assemble a parcel-level panel dataset of oceanfront land in Oregon from 1990 to 2015 where we observe the location and timing of each armoring decision by eligible parcels and a rich set of variables representing physical characteristics of the land, previous decisions of neighboring parcels, and seasonal shocks. We employ both a two-way fixed effects linear probability model and a non-linear correlated random effects (CRE) model (Mundlak 1978; Lewis et al., 2011) with an exogenously defined spatial network and lagged spatial spillover effects to overcome identification issues that often confound estimation of peer effects (e.g., Manski 1993). Our econometric results suggest that spatial spillovers, both the potential for a negative externality and peer effects, significantly increase the probability of observing a private armoring choice. Next, we apply our non-linear CRE results in a Monte Carlo landscape simulation to test the implications of our results on future armoring decisions under SLR and policy scenarios. Our simulations offer three key insights: 1) spatial spillovers affect the temporal and spatial patterns of adaptation and prediction that ignores these impacts may significantly underestimate future armoring choices; 2) land-use policy interventions can significantly limit shoreline armoring; 3) SLR likely will increase predicted armoring and adds urgency for new policy prescriptions. A key contribution is our finding that spatial interactions between neighbors have a large influence on the armoring decision relative to the risk characteristics of the land. This result is new in a coastal adaptation setting and is consistent with findings on effects of spatial spillovers in agriculture (Lewis et al., 2011), residential development (Irwin and Bockstael 2002) and habitat conservation (Lawley and Yang 2015).

Our landscape simulations provide policy context for future coastal management decisions. We find naive geomorphological simulations of armoring (i.e., risk characteristics of land only) predict 37 to 97 percent less armoring totals over the next 40 years then models accounting for spatial spillovers. This suggests that increased armoring likely generates a feedback effect that further increase the impact of the spatial spillovers in all subsequent periods. Importantly, a counterfactual policy that relaxes current armoring restrictions in Oregon may result in significantly more armoring over the next 40 years (69

[1] Gopalakrishnan et al. (2017) find that interactions of two adjacent communities considering a nourishment decision may be impacted by alongshore transport that has potential to distribute sand from wide, nourished beaches to narrow, unnourished beaches. This spatial process may lead to under-investment in nourishment activities due to the positive externality created by one community's nourishment decision and a lack of coordination between communities.

percent) compared to continuation of the current land-use regulations, highlighting the critical role policy is likely to have in shaping our future coastlines. Lastly, when we simulate an aggressive SLR scenario with the relaxation of armoring restrictions, we find an additional increase of armoring by 5.4 percent.

The remainder of this paper proceeds as follows. Section 1 provides an overview of the institutional background of coastal adaptation options in Oregon and Section 2 walks through a conceptual model of the armoring decision. Section 3 presents our linear probability model, the correlated random effects model, and our identification strategy for estimating spatial spillover effects. Section 4 describes our data and Section 5 discusses our estimation results and robustness checks. Section 6 contains our landscape simulations that highlight the critical role of spatial spillovers and applies future policy and SLR scenarios to demonstrate the implications of our econometric results. The last section concludes and offers avenues for future research.

1. The Oregon Coast

The state of Oregon has 360 miles of coastline along the Pacific Ocean and the coastal zone is home to 225,000 people, less than 7 percent of the state's population. The focus of this work is Tillamook and Lincoln Counties, a continuous 102 mile stretch of shoreline along the north-central Oregon Coast where over 95 percent of recent armoring has occurred (Fig. 1). Sandy beaches front much of this coastline (e.g., 79 percent in Tillamook County; Mills et al., 2018) with sea cliffs present in some areas. Oceanfront homes are located along sandy beaches that are backed by either dunes or small bluffs. The public also has a significant stake in Oregon's sandy beaches due to the permanent recreation easement allowing unfettered public access to all beaches in the state granted by the 1967 Beach Bill.

Coastal hazards, especially erosion, have amplified recently due to increases in winter storm activity, sea-level rise, and the severity of El Niño−Southern Oscillation (ENSO) events (Mills et al., 2018). Beach nourishment, a common public policy response to erosion in other areas of the United States, has not been attempted in Oregon.[2] The state has no policy on nourishment, does not have a state funding mechanism, and the small size of coastal communities likely precludes raising the significant local matching funds necessary for federal nourishment projects (NOAA, 2000). Oregon's Statewide Land Use Planning Goals were implemented in the mid-1970s with Goals 17 and 18 focused on managing coastal development and limiting non-essential shoreline alterations. These goals promote nonstructural solutions to erosion with designs that minimize impacts to the environment, but do not offer design standards to meet this goal. This has limited implementation of erosion control measures on much of the Oregon ocean shoreline.

The lone exception exists within Goal 18.[3] This goal prohibits development in dunes and sandy beaches but allows oceanfront property owners the option for hardening the shoreline with rip-rap revetments (Fig. 2) if and only if the parcel was developed prior to January 1st, 1977. This armoring fixes the shoreline in place and is the only adaptation option for many

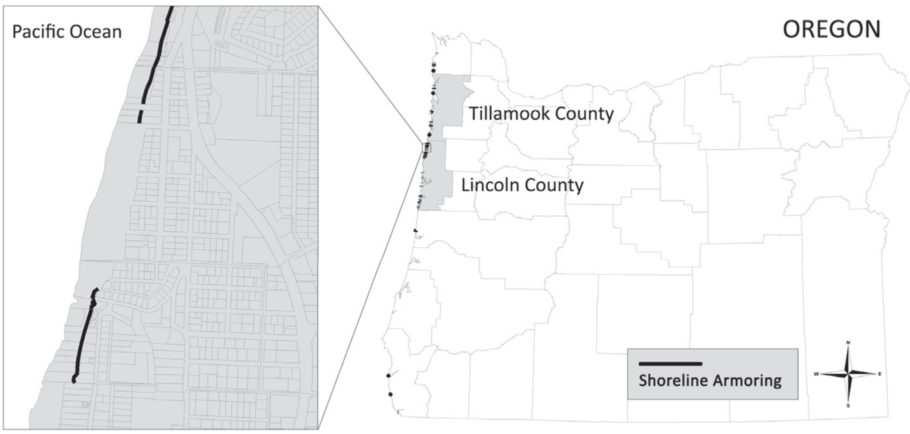

Fig. 1. Oregon shoreline armoring map. Black lines indicate installation of shoreline armoring as of 2014. Majority of armoring occurs in Lincoln and Tillamook counties (grey shaded and labeled on map). Lincoln County inset illustrates the spatial variability and clustering of installations on a parcel map.

[2] The Program for Study of Developed Shorelines at Western Carolina University maintains a database on beach nourishment that suggests Oregon is the only state in the U.S. with an ocean coastline that has not has a nourishment event. NOAA's National Beach Nourishment database records two locations in Oregon with nourishment events, one for navigation at the mouth of the Columbia River and one for breakwater placement at Port Orford.

[3] Goal 18 also allows for permits for dune grading, which is typically done not for erosion control but to improve ocean views of oceanfront homeowners. Dune restoration is also not common in Oregon and is only currently being done on federal land by the US Forest Service at Oregon Dunes National Recreation Area, nearly 15 miles from the nearest oceanfront residential development.

Fig. 2. Example of a shoreline protective structure. A rip-rap revetment in Neskowin, Oregon in April 2018. Photo by Steven J. Dundas.

homeowners in the state. Under Goal 18, approximately 50 percent of the 9050 oceanfront parcels in Oregon are eligible for armoring. As of 2015, only 22 percent of eligible parcels have exercised this option and approximately 3500 parcels retain eligibility for future armoring grandfathered under Goal 18.[4]

The Oregon Department of Land Conservation and Development (ODLCD) monitors eligibility for armoring by parcel. The Oregon Parks and Recreation Department (OPRD) is responsible for issuing armoring permits under Goal 18. The installation process requires a landowner to initiate an application with OPRD and hire a licensed geologist to assess the erosion risk of the parcel. The parcel inspection includes a determination on whether the structure on the property is at imminent risk from erosion and if so, recommendations on the type, location, and dimension of the protective structures. This information is processed through a formal review with OPRD and the agency makes a final decision on whether to grant or deny an application for armoring.[5,6]

2. Conceptual framework

We begin with the hypothesis that parcel characteristics (i.e., erosion rates, distance to shoreline) that convey the severity of risk and spatial interactions between neighbors (Anselin 2001) are likely to affect a landowner's decision to armor. The decision made for each parcel is also likely to have both direct and indirect spatial impacts on proximal parcels. Direct effects include a spatial externality, where the deflection of wave energy may accelerate erosion on nearby parcels. Indirectly, armoring decisions may generate a peer effect by providing observable information about costs, risks, and aesthetics to neighboring landowners.

We cast the private decision to install shoreline armoring as a real option model with a comparison of costs given an irreversible adoption decision, learning and uncertainty following Lewis et al. (2011):

$$NV_{it} = [ENPV(R_{it} = 1) - ENPV(R_{it} = 0)] - OPV_{it} + L_t(S_{it}, s_{it}) > 0, \tag{1}$$

where NV is the net value of parcel i at time t, $ENPV$ is the expected net present value to the landowner conditional on the choice of armoring (R), OPV is the option value for future armoring if parcel i is currently unarmored, and L is the learning

[4] The only other hardened structures on the oceanfront of Lincoln and Tillamook Counties are jetties at two major navigational inlets (Yaquina Bay in Newport and Tillamook Bay in Rockaway Beach). In both cases, the structures were built decades before our study timeframe and the land adjacent to the jetties are state or county parks.

[5] If unexpected storm damage occurs, a temporary emergency permit may be granted provided the landowner is eligible for shoreline armoring. Emergency permits must receive retroactive approval, or the landowner is forced to remove the structure. In addition, the state has granted several overrides to existing eligibility requirements. These exceptions are generally infrequent and related to community-level concerns, not individual parcels.

[6] Goal 18 is a particularly contentious issue that has made headlines in Oregon recently. At the center of this controversy is a house located in Rockaway Beach (Tillamook County) that is threatened with collapse due to severe erosion. An armoring permit had been denied due to ineligibility, leading to a two-year legal battle between the homeowner, the township, and state agencies. While this situation is currently an outlier, severe erosion and increased SLR continue to reduce buffers between the ocean and private coastal assets.

effect arising from neighboring parcel decisions to armor. This fixed cost of learning may be influenced by S, the number of a parcel's direct neighbors with a shared property line that are armored at time t and s, the number of armored neighbors that do not share a property line but are within a given radius of parcel i at time t. We interpret the effect of S as being comprised of both the direct (externality) and indirect (peer) spatial spillovers.[7] We interpret s as an indirect learning effect, or peer effect, as a landowner may learn about the effects of armoring from the decisions of those in their local area. The installation of armoring significantly alters the shoreline and should be directly observable by nearby neighbors or when present on the beach. Assuming homeowners will maximize the net value of their asset, the choice to install armoring is met when the net value of eq. (1) is greater than 0.

A parcel's NV can be specified further as a land-value (LV) function conditional on the decision to armor (R):

$$NV_{it} = LV\left(X'_{it}, S'_{it}, s'_{it}, \delta_t | R'_{it}\right) \tag{2}$$

where X is vector of observable parcel characteristics and δ_t is a control for shocks in value as a function of time. *A priori*, we expect $\left(\frac{\partial LV}{\partial X^+}\middle|R=1-\frac{\partial LV}{\partial X^+}\middle|R=0\right) \le 0$ and $\left(\frac{\partial LV}{\partial X^-}\middle|R=1-\frac{\partial LV}{\partial X^-}\middle|R=0\right) \ge 0$ where X^+ and X^- convey risk-reducing and risk-increasing land characteristics, respectively. Spatial spillovers from both direct and nearby neighbors are also likely to impact land value and there exists several arguments for why we expect these effects to be non-zero $\left(\frac{\partial LV}{\partial S_{it}}\middle|R=1-\frac{\partial LV}{\partial S_{it}}\middle|R=0\right) \ge 0$; $\left(\frac{\partial LV}{\partial s_{it}}\middle|R=1-\frac{\partial LV}{\partial s_{it}}\middle|R=0\right) \ge 0$.[8] Greater armoring counts may deflect wave energy to neighboring parcels, altering shoreline conditions. Additionally, at-risk coastal homeowners are likely to begin the permitting and installation process before realized damages occur. Combined with the uncertainty of the severity of coastal risk arising from seasonal variation in storm events and along-shore sediment transport, homeowners are likely to utilize nearby neighboring decisions (s) to inform their own decision regarding protection strategies against future risks.[9]

To illustrate the spillover effect, we construct a simple model by letting $t = 1$, $i \in (1, \ldots, N)$ and specifying P_x and P_R as exogenous price vectors for X and R (defined as a continuous good for simplicity). With a given income level I, each coastal landowner is faced with the decision to maximize their net value as a function of parcel characteristics and the armoring decision:

$$Max_{X_i,R_i}\ NV_i(\bullet) \tag{3}$$

$$Subject\ To:\ I_i = P_x X_i + P_R R_i;\ \forall\ i = 1, \ldots, N$$

Optimal decision quantities for X and R are characterized by the first order conditions (F.O.C.) for each parcel i.

$$\frac{\partial NV_i}{\partial R_i} = \lambda P_R \tag{4}$$

$$\frac{\partial NV_i}{\partial X_i} = \lambda P_X \tag{5}$$

where λ is the Lagrange multiplier. Joint maximization of net values for all landowners to identify the decision criteria for socially optimal levels of armoring and consumption is:

$$Max_{X_i,R_i}\ \sum_{i=1}^{N} NV_i(\bullet) \tag{6}$$

$$Subject\ To:\ \sum_{i=1}^{N} I_i = P_x \sum_{i=1}^{N} X_i + P_R \sum_{i=1}^{N} R_i$$

The F.O.C. from the joint Lagrangian optimization are:

[7] With currently available data, we are unable to separately identify the two effects posited to be contained with a measurement of S. We would need to conduct a survey of oceanfront landowners to accurately deconstruct these spillover effects.

[8] By design, an increase in the count of armored neighbors to parcel i would be equivalent to the decision of parcel j to install armoring $\left(\frac{\partial LV}{\partial S_i} = \frac{\partial LV}{\partial R_j};\ i \neq j\right)$ if i shares property line with j.

[9] There are multiple studies stressing the importance of social conditions and outcomes on individual decisions. Utilizing a framework of imitators and optimizers, Conlisk (1980) demonstrates that imitating behavior may be an optimal choice given uncertainty and large costs. Anselin (2001) has also demonstrated the importance of spatial effects in microeconomic applications.

$$\frac{\partial NV_i}{\partial R_i} = \lambda' P_R - \frac{\partial \sum_{j=1}^{N-1} NV_j}{\partial R_i} \; ; \; \forall \, j \neq i \tag{7}$$

$$\frac{\partial NV_i}{\partial X_i} = \lambda' P_X \tag{8}$$

The decision rule governing the choice of R between the market decision and the social planner differs by the second term of the derivative in eq. (7), which is the spatial externality from the installation of shoreline armoring. This term is negative by assumption and increases the threshold of damages required to install shoreline armoring. That is, a higher benefit must accrue to parcel i to offset the damages that are inflicted upon all other parcels by i's decision. Current market conditions, which do not require individual landowners to consider spillovers, may lead to excessive armoring decisions if the externality is not internalized.

3. Empirical model

We cast the landowner decision for private coastal adaptation as a discrete choice problem of whether to install shoreline armoring. The reduced-form model builds off the framework of Lewis et al. (2011) and addresses a variety of identification concerns with spatial interactions. The "reflection" problem creates an identification issue in linear models when the group-average is used to explain individual decisions (Manski 1993). When utilizing the count of peers, rather than the average outcome of the peers, we avoid this problem (e.g., Lewis et al., 2011). There may be issues associated with the endogeneity of group formation. We overcome this by introducing an exogenously defined adjacency matrix (A) specifying the peer-relationship between neighboring parcels. This process creates a unique peer-cohort for each parcel along the coast. Next, we are also concerned with the potential simultaneity in decision making between peers. We introduce a one-period lag (Kaustia and Rantala 2015) in neighboring decisions to avoid the contemporaneous influence of peers or shocks to peers. This fits with the context of shoreline armoring as the decision to armor is a multi-staged process that requires risk assessment inspections, permitting and an eventual build. For a given parcel, nearby landowners may observe this process which, in turn, may impact their decision in subsequent periods. Next, we control for influences that may arise from exogenous characteristics shared by the group, such as neighboring parcel elevation. Lastly, we acknowledge that unobserved, shared, and likely time-invariant individual and group characteristics may influence the decision process. Our estimation strategy utilizes both fixed effects and correlated random effects in separate models to address these concerns.[10]

We start by adding a composite error term to the land value function (eq. (2)):

$$NV_{it} = LV\left(X'_{it}, S'_{it}, s'_{it}, \delta_t | R'_{it}\right) + (\mu_i + \varepsilon_{it}), \tag{9}$$

where μ_i represents unobservable time-invariant characteristics of each parcel and ε_{it} is a standard *i.i.d.* normal random variable that varies across time and space. We specify the observable portion of the armoring decision first as a linear function:

$$LV(X_{it}, S_{it}, s_{it}, \delta_t, R_{it}) = X'_{it}\beta + \frac{\sum A_{ij} X'_{jt}}{m_i}\omega + S'_{it}\alpha_1 + s'_{it}\alpha_2 \; + \; \delta_t \; ; \; j \neq i, \; \in J(i), \tag{10}$$

where X contains observable parcel characteristics such as the short-term shoreline change rate, the distance from the home to the vegetation line, and mean elevation. The elements of the adjacency matrix (A) take a value of 1 if parcel i and parcel j are considered peers and is 0 otherwise. We further define $s'_{it} = \sum A_{ij} R'_{jt}$ and m_i as the total peer count. In this setup each parcel has their own unique, and externally defined group, where the peer count rather than the shared peer-average is utilized (e.g., Lewis et al., 2011). Controls for temporal shocks (e.g., storm events) are captured through δ_t. The specification in eq. (10) addresses the reflection problem, simultaneity, and group-influence but does not resolve endogeneity issues associated with unobserved characteristics.

We use a two-way fixed effects linear probability model to estimate the probability of installation. This approach uses a within-transformation of (10) to eliminate the unobserved time-invariant parcel characteristics (μ_i):

$$\Pr\left((R_{it} = 1) \,| X'_{it}, S'_{it}, s'_{it}, \delta_t\right) = \dot{X}'_{it}\beta + \sum \dot{S}'_{it-1}\alpha_1 + \sum A_{ij}\dot{R}'_{jt-1}\alpha_2 + \delta_t \tag{11}$$

The advantage of this approach when coupled with controlling for temporal effects (δ_t) is the reduction in bias associated with time-invariant unobservables. The linear probability model also permits straight-forward estimation and interpretation of marginal effects. The downside is the inability of the model to assess the impact of important time-invariant controls,

[10] This approach negates the need for the researcher to impose spatial structures through spatial weighting matrices or find time-varying instruments.

including the effects of neighboring geology and short-term shoreline change rates that may be important factors when simulating future armoring decisions.

As an alternative strategy, we use a non-linear probit model to estimate the probability of installation where $\Phi(\bullet)$ denotes the standard normal cumulative distribution function (CDF):

$$\Pr((R_{it}=1)\,|X'_{it},S'_{it},s'_{it},\delta_t,\mu_i) = \Phi\left(X'_{it}\beta + \frac{\sum A_{ij}X'_{jt}}{m_i}\omega + \sum S'_{it-1}\alpha_1 + \sum A_{ij}R'_{jt-1}\alpha_2 + \delta_t + \mu_i\right) \tag{12}$$

Eq. (12) is estimated using maximum likelihood techniques and we use the same strategies to avoid issues of reflection and simultaneity. In this model, any time-varying control will be a function of the composite error term, producing endogeneity concerns given the presence of μ_i. To account for these concerns, we use a correlated random effects (CRE) approach with the Mundlak-Chamberlain device to perform the role of a pseudo-fixed effect (Mundlak 1978; Chamberlain, 1982). This allows further decomposition of the composite error term by specifying the unobserved, time-invariant component (μ_i) as a linear function of the average of all time-varying observables ($\overline{X'}_i, \frac{\sum A_{ij}R'_{it-1}}{T}$) by parcel and an unobserved, mean zero normally distributed random variable (τ_i). Explicitly modeling the parcel-level effect using the average of time-varying observables allows for unbiased estimation with a more tenable assumption of orthogonality ($E[\tau,X] = E[\tau,\sum A_{ij}R'_{it-1}] = 0$). Our final non-linear model of the probability of armoring is expressed as:

$$\Pr((R_{it}=1)\left| X'_{it},S'_{it},\overline{X}_i,\overline{S}_i,\delta_t,\mu_i\right.) =$$
$$\Phi\left(X'_{it}\beta + \frac{\sum A_{ij}X'_{jt}}{m_i}\omega + \sum S'_{it-1}\alpha_1 + \sum A_{ij}R'_{jt-1}\alpha_2 + \delta_t + \left(\overline{X}'_i\gamma + \overline{S}'_i\theta_1 + \frac{\sum_{t=1}^{T}\sum A_{ij}R'_{it-1}}{T}\theta_2 + \tau_i\right)\right) \tag{13}$$

Inclusion of the Mundlak-Chamberlain device uses a pseudo-fixed effect to mitigate unobservable characteristics that would be associated with the time-varying measures. The estimates and interpretations of $\widehat{\beta}$ and $\widehat{\alpha}$ for all time-varying components is that of $\widehat{\beta}^{FE}$ and $\widehat{\alpha}^{FE}$ (Mundlak 1978). Under this identification strategy, we interpret vector estimates of $\widehat{\beta}$, $\widehat{\alpha}$, $\widehat{\omega}$ and $\widehat{\delta}$, while the Mundlak coefficients ($\widehat{\gamma}$ and $\widehat{\theta}$) have no interpretation though they serve as important controls.

In both (12) and (13), time-varying characteristics within X' convey attributes of risk and are interpreted as changes in a parcel's risk factors ($\widehat{\beta}$). Lagged neighboring armoring decisions may represent either an unobservable spatial spillover of local armoring ($\widehat{\alpha}_1$) or may serve as a peer effect (learning mechanism) through which homeowners may update their understanding of the benefits of armoring ($\widehat{\alpha}_2$). In equation (13), the effect of neighboring characteristics ($\widehat{\omega}$), correspond to the influence of peer characteristics on an individual parcel decision.

4. Data

As noted earlier, we focus our empirical application on two coastal counties in Oregon – Tillamook and Lincoln – where oceanfront armoring installation accounts for over 95 percent of the total permitted armoring between 1990 and 2015. The armoring decision is fundamentally irreversible and a low probability decision in a given year. In the 25-year period spanning our data, approximately 13 percent of eligible parcels armored. The OPRD permitting database captures all armoring permits along the coast from 1967 to present. This database includes an application date, permit number, parcel number, approval decision, permit type and structure type. Most structure types are identified as rip-rap revetments (Fig. 2). There are approximately 440 approved armoring permits in total.[11] ODLCD maintains an additional database tracking eligibility by parcel. Combining these two datasets, we can characterize each parcel by armoring eligibility and identify when armoring has occurred. Deed and tax records for all parcels were purchased from CoreLogic's University Data Portal. These data provide characteristics of the parcel (e.g., lot size) and existing structures (e.g., square footage). Projections of a parcel's real market value (RMV) were obtained from county tax assessor offices. Spatially explicit and time-varying variables for each parcel are generated using lidar data from 1998, 2002, 2009 and 2014 and GIS processes.[12] Derived time-variant and time-invariant measurements include building footprints, the distance from the footprint to the shoreline and actual vegetation line (the likely armoring location) and parcel elevation.[13] Shoreline change rates (feet per year; accretion/positive, erosion/negative) are assigned to each parcel using data from 50 m orthogonal transects along the Oregon Coast estimated in a recent U.S.

[11] Armored parcels for which no permit exists have been discovered, but are mostly pre-Goal 18 installations (i.e., before 1977) and do not impact our estimates post 1990.

[12] We assume that periods between measurements correspond to the most recent observation, except for periods prior to 1998 which are assumed to be at the 1998 measurement.

[13] We do not directly observe a parcel's underlying geology (dune or bluff-backed); however, the parcel elevation variable indirectly controls for this difference as bluff-backed parcels are likely situated at relatively higher elevations than dune-backed parcels (Ruggiero et al., 2013).

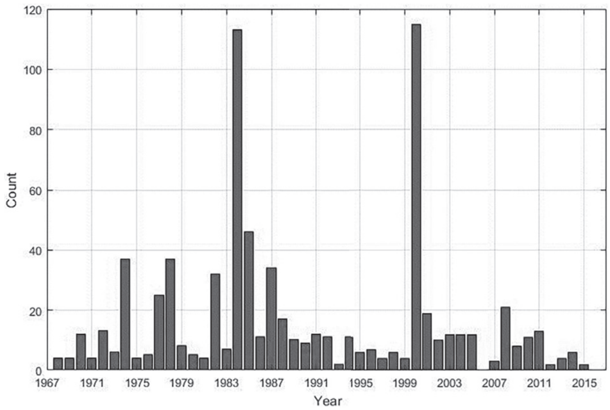

Fig. 3. Histogram of annual armoring counts in Oregon from 1964 to 2014. Extreme peaks correspond to ENSO events.

Geological Survey report (Ruggiero et al., 2013). These rates are time-invariant and represent short-term annual shoreline change estimated as an end-point rate between shoreline measures from 1967 to 1988 compared to a lidar-derived shoreline measure in 2002. The rates explicitly account for geomorphology (dune or bluff-backed) and use total water level (TWL) model estimates to correct for measurement error in historical shoreline positions.

Installation and permitting records are translated from calendar years to wave-years. A wave-year in Oregon is a 12-month period starting in April ending in March of the following calendar year. This allows the effects of cyclical storm seasons and wave cycles in Oregon (e.g., ENSO events) to be captured in a single period, rather than spanning across multiple time intervals. Historically, ENSO events occur approximately every 17 years and result in increased wave heights and total water levels along the Oregon Coast, leading to substantial increases in the volume of armoring. Fig. 3 displays historical armoring counts by year and the spikes in installation correspond to responses to ENSO events. In our robustness checks, we also control for the effect of increased water levels through a measure of the number of times a parcel experienced an exceedance to a predefined TWL.[14]

To quantify the impact of spatial spillovers, we create measures of neighbor armoring decisions over time from permitting data and GIS proximity tools. We explicitly capture the count of directly armored neighbors for each parcel (S) and the count of armored neighbors (excluding direct) within a defined radius (s) in each wave-year. We compile the data into a panel from 1990 to 2015. Unarmored parcels have 25 records, one for each wave-year. Each parcel is observed in every period until a decision to armor decision is made, at which point they are excluded from future period estimation. The final unbalanced panel consists of 2136 parcels eligible for armoring that were unarmored as of 1990. Of these parcels, 284 (13.3 percent) are observed to armor within the study timeframe. Table 1 provides summary statistics for eligible armored parcels, eligible unarmored parcels and ineligible unarmored parcels in Tillamook and Lincoln counties. Table 2 provides further detail regarding the geomorphological similarities in eligible Tillamook and Lincoln County oceanfront properties and economic similarities between the counties, demonstrating the suitability for pooling the counties in our analysis.

Among parcels eligible for armoring, there are distinct differences between parcels with armoring and those without. Parcels with armoring, on average, have a higher real market value. These armored properties, on average, are nearly sixty-five percent the mean elevation of parcels that have not yet armored. In addition, armored parcels experience short-term erosion rates nearly three times higher than those without. Fig. 1 illustrates the location of installed shoreline armoring in Oregon, with an inset highlighting the local variation in armoring that is common across Tillamook and Lincoln counties. Between both counties, we observe that the average parcel is eroding, though at a slightly faster rate in Tillamook County.

5. Estimation results

Estimates from our linear probability model (LPM) on the binary choice of armoring are presented in Table 3. Column (1) presents estimates of eq. (11) without additional considerations. We find the distance from the developed structure to the vegetation line is significant and negative. For every 1-foot increase in vegetation line distance, a house is 4.06e-06 percent less likely to armor. We next evaluate the role of direct neighbor decisions in the previous period (wave year) on the current armoring decision. We believe this effect to be a combination of spatial spillovers from installation (i.e., worsening erosion) and the peer effect associated with learning from neighboring actions over time. For each direct neighbor that armors, the likelihood of armoring increases 0.024 percentage points. We argue the peer effect, calculated as the total armoring of

[14] TWL time series were developed using the techniques described in Serafin et al. (2017). This measurement is only available for a subset of the population and thus is used only in a robustness check.

Table 1
Summary statistics by parcel eligibility for armoring.

	G18 Eligible						G18 Ineligible		
	Armored			Unarmored			Unarmored		
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.
RMV (000s)	284	1291.67	1420.85	1852	818.32	815.58	1489	548.33	1148.64
Acreage	284	0.78	6.87	1852	0.72	6.47	1489	11.16	91.25
Mean Elevation	284	19.93	15.70	1852	34.86	30.96	1489	55.07	77.29
Shoreline Change (ft/yr)[a]	284	−3.56	2.94	1852	−1.28	4.06	1489	−1.14	4.79
Distance to Shoreline (ft)	284	264.19	103.79	1852	409.79	196.08	1489	420.72	400.26
Distance to Vegetation Line (ft) (as of 2014)	284	70.11	34.39	1852	183.97	189.64	1489	326.14	535.86
Armored Direct Neighbors (as of 2014)	284	0.29	0.53	1852	0.27	0.99	1489	0.48	2.37
Armored Peers (2 km as of 2014)	284	47.32	42.86	1852	37.11	35.94	1489	21.19	30.78
Wave Exceedance of 5.5 m	144	17.90	34.39	644	59.93	158.93	–	–	–
Neighbor Mean Elevation	284	24.94	14.66	1852	34.13	22.60	1489	48.15	34.10

Note: Sample consists of parcels in Tillamook and Lincoln County that were unarmored as of 1990.
[a] Shoreline change is reported as a negative (eroding) or a positive (accreting).

neighbors in a 2 km radius, captures the spatial spillover associated with learning in the coastal adaptation process.[15] The peer effect is strong and significant, suggesting that as greater volumes of armoring appear in each parcel's neighborhood, the likelihood of a landowner choosing to armor increases. Each neighbor within a 2 km radius that installs shoreline protection increases the likelihood of armoring by 1.55e-04 percentage points. The marginal effects are small, but meaningful, given the mean likelihood of armoring is less than 1 percent for a given parcel in any period. Additionally, the installation decision is a repeat choice in each period for unarmored, eligible parcels. Small, compounding changes in the percentage of installation eventually increases total cumulative armoring. We also find evidence that interannual shocks are highly significant, with ENSO events having the strongest effect and increasing the likelihood of armoring by 0.058 percentage points. The ENSO effect corresponds to the observable increase in armoring in 2000 (Fig. 3).[16] In column (2) of Table 3 we present results from the LPM with interaction between short-term shoreline change rates and our time-varying controls. We do find evidence that greater erosion increases the likelihood of armoring for parcels with development nearer the shoreline.

Next, we present results from our CRE model (eq. (13)) that allows estimates of time-invariant parcel characteristics in Table 4. We fail to reject the null hypothesis that the random effect is zero through a likelihood ratio test, resulting in pooled estimation. Column (1) presents the armoring decision with parcel-specific controls, an ENSO shock, and dichotomous time controls (geomorphology model), restricting α_1 and α_2 to zero. Results suggest that higher-valued homes are more likely to armor, all else equal. A one-thousand dollar increase in parcel value increases the likelihood of installation by 2.40e-06 percentage points. Parcel acreage is significant with non-linear effects suggesting the size of the property is a determinant in the protection decision.[17,18] Each additional acre, at the mean, decreases the likelihood of installation by 2.43e-03 percentage points. Erosion rates are significantly associated with higher likelihood of observing an armoring decision. For every foot increase in erosion per year, the likelihood of armoring increases by 4.93e-04 percentage points. Homes that are further from the shoreline are significantly associated with a lower likelihood of armoring. Each foot setback from the shoreline decreases the likelihood of armoring by 9.05e-06 percentage points. The erosion and shoreline measures are likely indicators of risk, which conform in directional effect to our *a priori* expectations and agree with the interpretation from the two-way fixed effects LPM estimates. The ability to protect a home's value is likely associated with higher benefits of installation and conforms to our *a priori* expectation on directional effects. We continue to find a strong and significant effect related to *ENSO* shock. Lastly, we also find evidence that neighboring characteristics are significant. For each 1-foot increase in the mean elevation of the neighbors is associated with a 9.48e-05 percentage point reduction in the likelihood of armoring. Neighboring attribute influence may occur when a homeowner is considering the likelihood of a neighboring installation.

[15] We choose 2 km as a realistic peer-network choice based on the assumption that homeowners are likely to observe neighboring effects as far as 1 km in each direction from their own shoreline. Robustness checks on buffer size suggest any choice between 1 km and 3 km would have comparable statistical significance and effects (see Table 6).

[16] There is also an ENSO event in 1983 that led to a significant increase in armoring in 1984 (Fig. 3). We only observe one ENSO event in our post-1990 data. Subsampling the data and excluding the seasonal event from any subset of data fails to capture the magnitude of such events.

[17] We do not observe parcel-level variation in cost of armoring installation. In our conversations with relevant state agencies and local engineering firms, we learned that armoring is a relatively inexpensive investment when compared to the value of the structures protected, ranging from $30,000 to $50,000 per parcel, or about 5−7 percent of the value of an oceanfront parcel.

[18] Utilizing ArcGIS, we calculate a measure of shoreline length through constructing parcel-based polygons for all parcels. We then measure the length of the polygon that is proximal to the shoreline for each parcel. For robustness, we calculate the acreage for each parcel polygon and estimate eq. (13) with a quadratic shoreline length and restricting our sample to those parcels where calculated acreage is within 20% of actual acreage. This restriction reduces our sample from 46,550 to 28,907. Our key variables are largely unchanged, while the effect of acreage loses significance and the effect of shoreline length is positive and significant and shoreline length squared is negative and significant. This suggests that the larger the property to protect, the more likely a homeowner will protect, although at a diminishing rate which may be related to the costs associated with armoring a longer shoreline. Results are presented in Table 5, column 5.

Table 2
Geomorphology and economic summary statistics by county.

	Tillamook County			Lincoln County		
	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Panel A: Parcel Geomorphology						
Minimum Elevation (ft)	845	17.86	22.89	1291	24.36	27.68
Maximum Elevation (ft)	845	31.52	43.32	1291	51.80	33.32
Mean Elevation (ft)	845	24.59	30.92	1291	38.29	27.78
Acres	845	0.57	4.56	1291	0.83	7.53
Shoreline Change (ft/yr)[a]	845	−2.42	4.19	1291	−1.03	3.77
Distance Shoreline (ft)	845	436.73	220.34	1291	360.13	165.80
Distance to Vegetation Line (ft) (As of 2014)	845	274.80	386.02	1291	126.27	112.30
Direct Neighbor Average (As of 2014)	842	0.15	0.47	1291	0.36	1.14
Peer (2 km) Armor Average (As of 2014)	845	32.33	31.85	1291	42.48	39.65
Installation	845	0.17	0.38	1291	0.11	0.31
Panel B: Economic Characteristics[b]	Tillamook	Lincoln				
Population (in 2019)	27,036	49,962				
Median Income (2019$)	$47,500	$46,061				
Median Home Value (2019$)	$240,000	$233,400				
Percentage Bachelor's Degree	21.0%	24.1%				
Population Density (per mi^2)	22.9	47.0				
Average Commute Time (minutes)	18.7	18.3				
Poverty Rate	13.2%	13.6%				
Percentage White	93.4%	89.6%				

Note: Sample consists of parcels in Tillamook and Lincoln County that were unarmored as of 1990.
[a] Shoreline change is reported as a negative (eroding) or a positive (accreting).
[b] Economic characteristics obtained from U.S. Census Bureau.

Table 3
Two-way fixed effects linear probability model results.

	(1) No Interactions	(2) Interactions
Distance Vegetation (ft)	−4.03e-06 ***	−8.12e-06 ***
	(1.12e-06)	(1.34e-06)
Distance Vegetation X Shoreline Change (ft/yr)		−1.10e-06 ***
		(2.80e-07)
Average Time	1.13e-02	1.13e-02
Storm Event	5.76e-02 ***	5.76e-02 ***
	(5.08e-03)	(5.08e-03)
Lagged Direct Neighbors	2.43e-02 ***	2.40e-02 **
	(6.20e-03)	(9.51e-03)
Lagged Direct X Erosion (ft/yr)		−9.75e-05
		(1.89e-03)
Lagged Peer Neighbors	1.55e-04 ***	1.77e-04 *
	(3.50-e05)	(8.55e-05)
Lagged Peer X Shoreline Change (ft/yr)		5.66e-06
		(1.87e-05)
Constant	−1.58e-02 ***	−1.58e-02***
	(1.78e-03)	(2.36e-03)
N	46,055	46,055

Standard errors in parentheses. *p < 0.05, **p < 0.01, ***p < 0.001.
Average time coefficient is an average of all non-ENSO event years.

In column (2), we estimate α_1 from eq. (13) to evaluate the role of direct neighbor decisions in the previous wave year on current armoring decisions (direct model). Our results suggest a strong and significant effect that increases the armoring likelihood with every direct neighbor choice, similar to the effect found in the LPM model. Each additional direct neighbor that chooses to armor increases the likelihood of armoring by 0.018 percentage points. In column (3) we estimate α_2 from eq. (13) to assess the role of the peer effect in the decision process (peer model). Under this specification, each direct neighbor armoring and each peer armoring increase the likelihood of armoring by 0.015 and 3.79e-04 percentage points respectively. Results suggest that in addition to the effect of direct neighbors, the peer effect is significant and increases the likelihood of armoring as additional peers engineer their shoreline. The sign, relative magnitude, and significance on key variables remain similar across all three specifications. Akaike information criterion (AIC) provides support for the selection of the peer model (column 3) compared to the geomorphology and direct models.

These results illustrate the many factors that coastal landowners face when considering the decision to mitigate shoreline erosion. In the absence of neighboring effects (i.e., parcels without any armoring in their neighborhood), the decision is based on risk conveyance factors, property values and random shocks to the system (i.e., ENSO events). A generalization of our

Table 4
Non-linear correlated random effects probit results.

	(1) Geomorphology Model	(2) Direct Model	(3) Peer Model
RMV (000s)	1.88e-04 ***	1.75e-04 ***	1.67e-04 **
	(4.37e-05)	(4.19e-05)	(5.01e-05)
Acres	−0.19 ***	−0.18 ***	−0.13 *
	(4.95e-02)	(4.90e-02)	(6.28e-02)
Acres Squared	1.60e-03 ***	1.44e-03 ***	1.05e-03 *
	(4.18e-04)	(4.14e-04)	(5.30e-04)
Mean Elevation (ft)	−9.88e-04	−8.51e-04	−2.63e-03
	(1.76e-03)	(1.91e-03)	(1.95e-03)
Shoreline Change (ft/yr)	−3.87e-02 ***	−3.84e-02 ***	−5.66e-02 ***
	(8.20e-03)	(8.58e-03)	(9.14e-03)
Distance Shoreline (ft)	−7.12e-04 **	−6.11e-04 *	−9.31e-04 **
	(2.56e-04)	(2.63e-04)	(3.02e-04)
Distance Vegetation (ft)	1.25e-03	1.21e-03	2.12e-03
	(1.06e-03)	(9.96e-04)	(1.22e-03)
CRE Vegetation	−7.84e-03 ***	−8.45e-03 ***	−9.23e-03 ***
	(1.37e-03)	(1.22e-03)	(1.51e-03)
Average Time	0.25	−0.03	−0.41
Storm Event	1.43 ***	1.23 ***	1.21 ***
	(0.19)	(0.15)	(0.15)
Lagged Direct Neighbors		1.45 ***	1.27 ***
		(0.15)	(0.17)
CRE Direct		−1.72 ***	−1.64 ***
		(0.20)	(0.22)
Lagged Peer Neighbors			3.22e-02 ***
			(2.93e-03)
CRE Peer			−2.47e-02 ***
			(2.82e-03)
Neighbor Mean Elevation (ft)	−7.45e-03 ***	−8.65e-03 ***	−5.96e-03 **
	(1.59e-03)	(1.65e-03)	(1.85e-03)
Constant	−2.06 ***	−1.73 ***	−1.82 ***
	(0.20)	(0.18)	(0.19)
N	48,121	46,055	46,055

Standard errors in parentheses. *p < 0.05, **p < 0.01, ***p < 0.001.
Average time coefficient is an average of all non-ENSO event years.

results suggests that characteristics which place a structure at greater risk are more likely to lead to a parcel armoring. ENSO events, which are infrequent and generate seasonal high wave climates associated with shifts in large volumes of sand, are highly influential in the armoring decision.

Armoring decision models external to economics typically rely on triggers based on physical characteristics of the land (e.g., Lipiec et al., 2018). In other words, when predicting armoring, the modeler will set limits on characteristics (such as distance to the shoreline) and assume once a parcel measurement crosses this threshold, the decision would be made. In classic economic decision models, the combination of ENSO events and risk characteristics would determine the patterns of armoring. However, these modeling processes are unlikely to reflect the reality that a landowner may experience an externality related to a neighbor's land-use decision or that they are likely to learn from observing such decisions. When we introduce spillover effects to the model, the effect of key geomorphological measures on the probability of armoring remain significant but are reduced in magnitude. The spillover effects tends to be larger in magnitude relative to other modeled effects. An important conclusion is that models of coastal adaptation using only land characteristics and temporal shocks may miss the impacts of spillovers, which alter temporal and spatial patterns of decision-making.

5.1. Robustness checks

We assess our modeling assumptions and specifications through a series of robustness checks. First, we evaluate the sensitivity of our results based on simultaneous peer effects, lagged peer effects and neighboring effects on estimation in Table 5. Column (1) illustrates the use of simultaneous neighboring armoring decisions. Results are consistent with our decision to avoid contemporaneous issues of installation and unobserved shocks through lagging the neighboring decisions (column 2). To test the influence of neighboring attribute influence, we add neighboring elevation to generate our preferred specification (column 3). We also incorporate data on parcel-specific annual TWL exceedances to account for an additional dimension of erosion risk that may influence armoring decisions (column 4). TWL measures the number of times in a year that a model predicts water levels rise above a given threshold (Serafin et al., 2017) and as such, this model excludes annual controls but incorporates a time trend. The addition of TWL to the model lowers the magnitude of the effect of direct neighbors, possibly capturing better local variation in risk impacting armoring decisions. The erosion effect strengthens as well, which would further add to the likelihood of armoring in areas with accelerating erosion. Unfortunately, TWL measures

Table 5
Robustness checks: Impacts of identification strategy on correlated random effect estimates for key controls.

	(1) Simultaneous	(2) Lagged	(3) Lagged + Neighbor	(4) TWL less Time[a]	(5) Shoreline Length
Erosion (ft/yr)	−5.70e-02 ***	−6.21e-02 ***	−5.66e-02 ***	−0.20 ***	−4.99e-02 ***
	(8.46e-03)	(8.79e-03)	(9.14e-03)	(3.98e-02)	(1.22e-02)
Distance Shoreline (ft)	−7.93e-04 **	−7.87e-04 **	−9.31e-04 **	−2.66e-03 ***	−1.01e-03 **
	(2.81e-04)	(2.91e-04)	(3.02e-04)	(5.46e-04)	(3.96e-04)
Direct Neighbors	1.17 ***	1.20 ***	1.27 ***	0.86 **	1.28 ***
	(0.15)	(0.17)	(0.17)	(0.29)	(0.17)
CRE Direct	−1.52 ***	−1.58***	−1.64 ***	−1.63 **	−1.59 ***
	(0.20)	(0.22)	(0.22)	(0.59)	(0.25)
Peer Neighbors	3.39e-02 ***	3.32e-02 ***	3.22e-02 ***	3.19e-02 ***	3.52e-02 ***
	(3.00e-03)	(2.98e-03)	(2.93e-03)	(8.52e-03)	(3.87e-03)
CRE Peer	−2.67e-02 ***	−2.53e-02 ***	−2.47e-02 ***	−7.49e-02 ***	−2.53e-02 ***
	(2.92e-03)	(2.85e-03)	(2.82e-03)	(1.45e-02)	(3.94e-03)
Neighboring Elevation (ft)			−5.96e-03 **	−7.38e-03	−1.06e-02 ***
			(1.85e-03)	(4.29e-03)	(2.15e-03)
TWL Exceedance				7.74e-03 ***	
				(2.41e-03)	
CRE TWL				−1.48e-02 ***	
				(3.82e-03)	
Shoreline Length (ft)					1.38e-02 ***
					(4.13e-03)
Shoreline Length Squared (ft)					−8.06e-05 ***
					(2.53e-05)
N	48,121	46,055	46,055	16,699	28,907

Standard errors in parentheses. *p < 0.05, **p < 0.01, ***p < 0.001. [a] denotes a change from time effects to quadratic time trend with ENSO indicator variable.

are only available for a small subset of parcels in our two-county study area. Even with the addition of a fine-scale, temporally varying measure of parcel risk, our primary controls remain consistently signed and comparable in magnitude and significance.

There are concerns about the endogenous nature of using real market value (RMV) given local adaptation decisions capitalize into home values (Dundas 2017; Qiu and Gopalakrishnan 2018; Dundas and Lewis 2020). This does not create a concern in the LPM model (eq. (11)) where time-invariant valuation measures are purged through the within transformation. However, the CRE probit (eq. (13)) retains the potentially endogenous control. Model results remain unchanged with and without the inclusion of the potentially endogenous regressor.

The adjacency matrix (A) in eqs. (11) and (13) is a modeling choice and theoretical guidance is limited on the extent or recommended peer-circumference. We therefore test the sensitivity of our choice to varying buffer sizes. We specify this matrix to extend 1 km in each direction (up to 10 km diameter; Ells and Murray 2013) to create a unique set of peers for each parcel. Table 6 presents two-way fixed effect LPM results with varying adjacency matrix choices between 1 km and 10 km. Despite the choice of peer-circumference, risk characteristics and direct effects remain significant and consistent in magnitude. In general, the magnitude of the peer-effect diminishes as the circumference is increased. Statistical significance decreases at a peer-effect of 4 km and disappears by 10 km. Although not reported here, we also estimate a Spatial Durbin Model that incorporates a weighting matrix to control for spatially endogenous interactions of neighbor decisions and also uses that matrix to account for spatial interactions in the error term. Utilizing an inverse distance weighted matrix, we find

Table 6
Impacts on the choice of the adjacency matrix.

	Distance to Vegetation	Direct Neighbors	Peer Effect
1 km	−2.98e-06 ***	2.06e-02 ***	6.64e-04 ***
	(1.07e-06)	(6.24e-03)	(1.11e-04)
2 km	−4.06e-06 ***	2.43e-02 ***	1.55e-04 ***
	(1.12e-06)	(6.20e-03)	(3.50e-05)
3 km	−4.42e-06 ***	2.50e-02 ***	8.23e-05 ***
	(1.15e-06)	(6.19e-03)	(2.24e-05)
4 km	−4.31e-06 ***	2.51e-02 ***	5.89e-05 **
	(1.14e-06)	(6.19e-03)	(1.86e-05)
6 km	−4.19e-06 ***	2.52e-02 ***	4.87e-05 *
	(1.13e-06)	(6.19e-03)	(1.90e-05)
8 km	−4.12e-06 ***	2.52e-02 ***	5.04e-05 **
	(1.13e-06)	(6.19e-03)	(1.78e-05)
10 km	−4.07e-06 ***	2.54e-02 ***	3.21e-05
	(1.13e-06)	(6.19e-03)	(1.73e-05)
N	46,055	46,055	46,055

Standard errors in parentheses. *p < 0.05, **p < 0.01, ***p < 0.001.

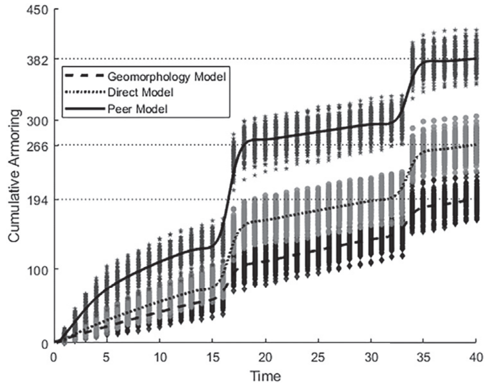

Fig. 4. Peer effect simulation results. Cumulative installation counts by model simulation presented for the geomorphology model (dashed), the direct model (dotted), and the peer model (solid). Mean number of armored parcels for these models 194, 266, and 382, respectively. All simulation results correspond to 200 iterations and the lines are fitted with a smooth spline.

further evidence of a positive and significant relationship of neighboring armoring decisions on an individual homeowner armoring decision. However, this approach requires assumptions on the structure of the spatial effect.

6. Simulating coastal futures

Due to the significance of spatial spillovers in our econometric results, we conduct landscape simulations to better understand the time path and spatial patterns of armoring decisions in a policy-relevant context. Our simulations offer probabilistic outcomes of future armoring along the Oregon Coast and generate distributions of the counts of new armored parcels in Tillamook and Lincoln counties over a 40-year period. Simulations offer three key results with respect to armoring decisions: 1) spatial spillovers significantly impact future land-use patterns, 2) land-use policy is a critical determinant of future armoring counts and 3) SLR is likely to increase future armoring.

Our process uses Monte Carlo methods (Lewis and Plantinga 2007; Lewis et al., 2011) to iterate the probabilistic installation decision of armoring informed by our econometric model results. We initiate a random draw from eligible, unarmored parcels in period *t*, where we estimate the probability of armoring based on the influence of parcel characteristics, spatial spillovers and time controls. If a parcel has eroded, on average, for the last 50 years we assume this trend will continue and update the setback distance from the vegetation line in each future period. For simplicity, we assume parcels with an accreting beach are stationary. In each period, the number of lagged neighboring armored parcels is updated for all parcels that remain unarmored. We include an average temporal effect and incorporate an ENSO event every 17 years. Armoring status is determined by comparison of the results between a Uniform (0,1) draw and the estimated probability of installation from eq. (13). The random uniform draw in this process accounts for the unobserved and stochastic nature of our process. If the probability estimation exceeds the uniform draw in a given period, then the parcel is designated as armored. This process iterates through the entire set of eligible, unarmored parcels in Tillamook and Lincoln counties in each time period.

We use coefficients from the nonlinear CRE probit models for all simulation scenarios for two reasons. First, a simple static version of the CRE probit has reliable in-sample predictive power, with a range of outcomes that bound historical armoring levels.[19] Second, as noted previously, the use of correlated random effects controls for time-invariant unobservables similar to a fixed effect but also allows consistent estimation of important time-invariant characteristics, like shoreline change rates. This allows us to simulate scenarios accounting for future impacts affecting the armoring decision related to climate change and SLR.

Our baseline simulation assumes key inputs external to the shoreline distance do not change over time, keeps the status quo land-use policy (Goal 18) and does not account for future SLR to first illustrate the impact of spatial spillovers on future armoring decisions. We simulate the landscape using parameters from the geomorphology model (Table 4, column 1), the direct neighbor model (Table 4, column 2), and our preferred peer model with spillover effects up to 2 km (Table 4, column 3). Simulation outcomes are illustrated in Fig. 4 where a smoothed spline is added across the 200 iterations for each model.[20] All three models exhibit the ENSO-related spike at periods t = 17 and t = 34. The geomorphology model conforms to *a priori* expectations illustrating the low, nearly uniform probability over time, which produces a smooth and gradual increase in total

[19] On average, the static CRE probit model of historical armoring bounds actual observed armoring, but slightly under-predicts (8%) on average. By comparison, similar in-sample simulation with LPM models tend to overpredict historical armoring by up to 35%. With low probabilities of land-use conversion, the choice of distribution could alter the probability of installation.

[20] Future simulations with the LPM model demonstrate similar results after 40 years, but the average linear result is 19.9% higher than the non-linear result, consistent with our in-sample prediction exercise suggesting linear models are likely to overestimate armoring counts.

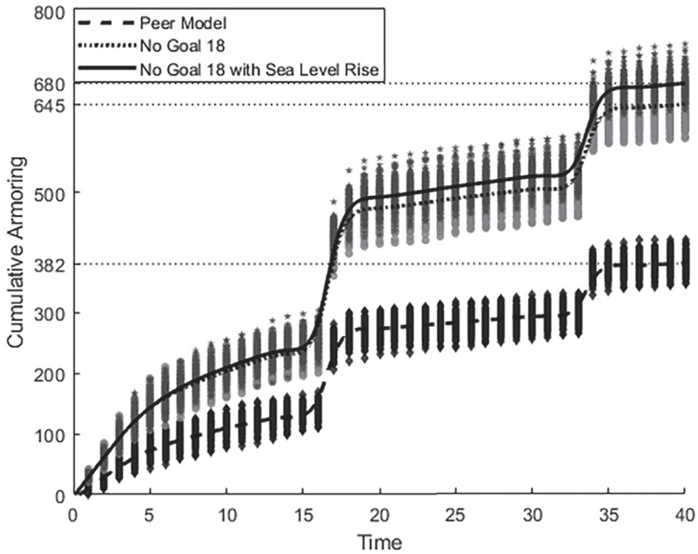

Fig. 5. Simulation of counterfactual Goal 18 policy removal and sea-level rise. Cumulative installation counts by model simulation presented for the peer model (dashed), a counterfactual with no Goal-18 policy (dotted), and the counterfactual with sea-level rise (solid). Mean number of armored parcels, respectively are 382, 645, and 680. All simulation results correspond to 200 iterations and the lines are fitted with a smooth spline.

armoring for non-ENSO time periods. The direct model introduces a feedback effect based on the cumulative decisions of adjacent properties in prior periods. This creates a slightly steeper ascent in cumulative armoring in non-ENSO time periods that grows over time. This difference from the geomorphology model is driven by small-scale clustering activity that leads to more localized armoring pressures. The ENSO shock closes the gap between the geomorphology model and the direct model in the 17th time period. However, as more adjacent parcels armor, the localized spillover effects grow which contributes to a greater divergence in model predictions over longer periods of time. After a 40-period simulation, the direct model produces, on average, 37.1 percent more armoring than the geomorphology model (266 compared to 194 parcels).

Our preferred model, which adds peer effects from non-direct neighbor armoring, produces substantial differences in the temporal pattern of armoring and the cumulative count. In early periods, the peer model generates more armoring and produces neighborhood clustering. This divergence between models continues to widen as each year produces new armoring, which further strengthens the influence of peer effects and leads to higher armoring counts. ENSO events do not close the gap between models because they help to reinforce the cumulative effect of peer decisions in the preferred model. In total, the peer model predicts 96.9 percent and 43.6 percent more armoring than the geomorphology model and direct model, respectively. This suggests naive models that ignore spillovers and neighbor interactions may significantly underestimate armoring counts over longer periods of time, particularly when high-resolution future estimates of shoreline characteristics are unavailable. In addition to underestimating cumulative armoring projections, not accounting for spatial interactions will fail to capture unique spatial and temporal patterns in private coastal adaptation decisions.

6.1. Applications: policy scenario and SLR-induced adaptation

A primary aim of Oregon's State Planning Goal 18 is the prohibition of armoring to preserve public good elements (recreational access and aesthetics) of the Oregon Coast. However, given the current volume of eroding parcels and increasing risk from SLR, potential changes to Goal 18 are being discussed that could lead to relaxing regulations in areas that meet certain criteria.[21] We illustrate the importance of policy by simulating a counterfactual scenario that eliminates Goal 18's armoring prohibition and incorporating data on ineligible parcels. Policy removal would increase armoring an additional 68.8 percent (Fig. 5). Current Goal 18 armoring prohibition would prevent 261 parcels (on average) from armoring over the 40-year simulation with the peer model. This preservation of the natural shoreline accounts for approximately 7.3 percent of Lincoln and Tillamook oceanfront properties. Undoubtedly, advocates of coastline preservation would view this restriction as a success but that leaves hundreds of landowners vulnerable to erosion and potential irreversible property losses in the short term. Furthermore, ENSO events induce armoring in areas without previous armoring installations, which then potentially accelerates clustering of future armoring decisions due to spillover effects. This suggests that periods following cyclical seasons of high water levels and wave action may lead to greater pressure on legislative controls to restrict armoring. These

[21] In 2019, ODLCD convened multiple focus groups of coastal managers, scientists, and stakeholders to review equity concerns regarding shoreline armoring eligibility under Goal 18.

results may serve as a cautionary note to coastal managers of the potential inadequacies of using a single coastal management plan and the future of land-use legal challenges likely to occur along the Oregon Coast.

We then introduce a set of likely SLR-driven parameter updates on key variables from our model. We collect data on annual potential SLR over the next forty years in Lincoln and Tillamook counties from NOAA (Sweet et al., 2017). Decennial estimates of SLR are linearly deconstructed into annual changes.[22] For simplicity, we translate this effect into an equivalent reduction in mean parcel elevation (relative to sea-level) by period. Next, we obtain shoreface slope data relative to all parcels in the two counties (Di Leonardo and Ruggiero 2015). We then apply the Bruun rule and estimate the accompanying recession of the shoreline based on SLR and shoreface slope $\left(Shoreline\ Change_i = \frac{Sea\ Level\ Rise}{Shoreface\ Slope_i}\right)$ (Schwartz, 1967). All parcels receive the same SLR treatment, however the impacts on the shoreline recession vary by individual parcel given variation in shoreface slopes. While we use a relatively aggressive estimate of SLR, our approach is likely to produce conservative results. We assume that annual storm and seasonal events over the last 24 years are constant when projecting into the future, despite evidence suggesting increased severity in the future. We also assume that ENSO events will match historical events in intensity. Lastly, we hold shoreline change rates constant due to an inability to justify parcel level rate changes as high-resolution estimates of future erosion patterns are not currently available.

Fig. 5 illustrates cumulative armoring totals for SLR effects (loss of shoreline, elevation change). Results suggest total armoring, in the absence of Goal 18, increases from 645 parcels to 680 (5.4 percent) after 4 decades with the SLR scenario. While only Goal 18 eligible parcels are currently permitted to armor, SLR will impact all parcels regardless of eligibility. This result simultaneously illustrates the power of legislative prohibition of armoring in preserving the coast, while also providing a forewarning of the magnitude of climate change induced coastal adaptation likely needed to maintain current development and land-use patterns in the future.

7. Conclusion

We develop a conceptual framework and empirical approach to model private coastal adaptation decisions through shoreline armoring. This framework introduces geomorphological and socioeconomic factors that are likely to play a role in determining spatial and temporal patterns of private coastal protection decisions. We demonstrate a theoretical basis for why parcel-level private armoring decisions are likely to lead to a negative spatial externality and induce excessive armoring. Our empirical results suggest parcel characteristics that convey risks to development are associated with a higher likelihood of armoring. Importantly, we demonstrate that spillover effects within a neighborhood, either through a learning mechanism or avoidance of spatial externalities, are highly significant in the decision process. Ignoring spillover effects will tend to significantly underestimate armoring counts and over-disperse armoring patterns (i.e., not produce clusters). These results are significant findings as the timing and clustering of armoring has important implications for potential policy changes that impact private protection options and provision of public goods.

Coastal management in the future is likely to be a mix of public and private adaptation to climate change. The commonly used public strategy of beach nourishment depends on a cyclic series of costly replenishment events to maintain coastal protection. Shoreline armoring (which is the dominant strategy utilized on the Oregon Coast) is a relatively affordable private investment in a durable good that provides protection from erosion at the scale of an individual parcel. Our results provide new insights into private adaptation decisions where negative externalities and peer effects may produce more adaptation than socially optimal. When neighboring communities interact, beach nourishment may lead to a positive-externality of sand-flow from nourished beaches to more-narrow beaches (Smith et al., 2009; Gopalakrishnan et al., 2017), resulting in an undersupply of public adaptation. Aside from coastal protection, these contrasting options may also impact the provision of public goods. Nourishment widens beaches and likely increases recreation and access, whereas shoreline armoring may disrupt beach access (i.e., shoreline impassable at high tides) and aesthetics in favor of protecting private property. With current expenditures on beach nourishment on the rise and predictions of large-scale investment in shoreline armoring in the near future (Neumann et al., 2015), there is significant importance in understanding how policy and management options influence private armoring decisions and how private and public adaptation policies may interact given the opposing incentive structures and potential externalities generated by these decisions. Understanding this dynamic is critical given the limited localized adaptation options available to respond to SLR. Managed retreat is another option that would allow the shoreline to move inland and include policy options such as relocation and buy-out programs (e.g. New Jersey Blue Acres Floodplain Acquisitions), habitat restoration (e.g., Sun and Carson 2020) or new land-use regulations. This option has only been identified in the economics literature to date as a potential alternative with several substantive institutional challenges (Kousky 2014).

Our findings suggest that policy matters and may be an effective tool to preserve the public good (beach access and natural landscapes). Oregon's Goal 18 is one such policy preventing unregulated armoring that may diminish public good characteristics of the state's beaches. Yet challenges remain. During the next strong ENSO event, many ineligible parcels would likely

[22] Projections for six global mean sea level (GMSL) rise scenarios are provided by NOAA (Sweet et al., 2017). These six global means range from "Low" to "Extreme". We utilize the "Intermediate-High" scenario for assumed SLR impact. Within each of the six GMSL scenarios, projections for the 17th, 50th and 83rd percentile are available. Our projections use the 50th percentile estimate.

face increased risks and potential loss of land and damage to homes and other structures. Our simulation results suggest mounting pressure to relax Goal 18 limitations to mitigate these damages. We predict over 645 parcels would armor over the next 40 years if deemed eligible. While we methodologically address the impacts of SLR through using elevation and setback distance changes, we likely under-represent effects on homeowners through worsening erosion rates and storm events. The reported SLR increase of 5.4 percent in armoring is a lower bound given the complex features of erosion risk and uncertainty and the data limitation that prevent us from fully incorporating all potential risk factors into our model. Nevertheless, we show that spillover effects are self-reinforcing and this influx of additional armoring would likely lead to densely clustered armoring segments along the Oregon Coast in the absence of policy.

These results are a first step to better understanding the drivers and optimal use of shoreline armoring as a strategy to mitigate impacts from erosion and SLR. In Oregon alone, there are still over 3500 oceanfront parcels that are eligible to install shoreline armoring. The timing and location of a parcel's decision to install armoring should influence the future geomorphological components of our model. Future work will include the integration of our discrete choice model with sediment transport dynamics in a coupled human and natural systems approach. With an integrated model, each period may be stepped forward and used to generate new sediment dynamics to then serve as inputs in each future period. A fully coupled, dynamic model of coastline geomorphology with human adaptation would provide a significant step forward in understanding the evolution of coastal development. In addition, appropriately accounting for realistic temporal and spatial clustering patterns will improve predictions and better inform coastal management policies.

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