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Defending the Shoreline: A Duration Model of Beach Re-Nourishment

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1. Introduction

Coastal communities face increasing threat from climate change as sea level rise accelerates long-term shoreline erosion rates and more frequent storms bring sporadic but huge damages to properties and infrastructure. Simultaneous trends in eroding beaches and growing coastal development have led to active coastal management policy to stabilize shorelines through the construction of seawalls, jetties, and beach nourishment. Beach nourishment – the process of periodically rebuilding an eroding section of a beach with sand dredged from offshore sand reserves or nearshore inlets (Dean, 2002, Landry, et al., 2003), is the dominant climate adaptation policy in most parts of the US Atlantic coast.

With increasing coastal development, the demand for beach nourishment continues to grow. Over the last few decades, the frequency of beach re-nourishment has increased from less than five nourishment projects per year in the 1930s to over 20 nourishment projects in the 2000s (Figure 1), which has resulted in an increasing volume of sand dredged for rebuilding beaches along the US Atlantic coast (Figure 2). Nourishment costs including fixed costs of infrastructure and project engineering and variable costs of nourishment sand are estimated between one and three million dollars per mile of shoreline (Dean, 2002). As a costly policy, beach nourishment in the US is primarily federally funded and implemented by the Army Corps of Engineers. Historically about two-thirds of the costs are supported by the federal expenditures (Trembanis, et al., 1999); appropriations for beach nourishment alone have exceeded $2.9 billion (Coburn, 2009). Nevertheless, shrinking federal budgets have increased the share of costs funded through state and local governments. US congressional sessions are considering further cut-backs in federal contributions toward beach nourishment (U.S. Senate Amendment #815). Reductions in federal subsidies for coastal adaptation can potentially result in dramatic changes in the coastal ecosystem and associated real estate markets (McNamara, et al., 2015).

Coastal natural capital stocks provide amenities at different spatial scales ranging from localized storm protection services to regional and global public goods in the form of recreational amenities, carbon sequestration and marine biodiversity. Shoreline stabilization through beach nourishment is implemented by dredging sand from offshore sand reserves or nearshore sand deposits along inlets and waterways. When beach nourishment is the dominant policy, economically viable deposits of nourishment sand is becoming a scarce common-pool resource extracted by multiple towns to maintain beach amenities and to supply inputs for industry (Höflinge, 2014). Because offshore reserves are typically harder to access and replenish slowly, they are like non-renewable resources. Sand deposits from inlets and river channels are periodically replenished and are renewable on shorter time scales. Though towns would prefer to access sand reserves that are closest to the beach in order to minimize costs, not all nearby sand reserves are suitable for beach nourishment. If sediment placed on a beach is significantly finer or coarser than its natural sand, it will be ineffective for nourishment. For example, Nags Head in the Outer Banks of North Carolina was not able to use the sand deposit in Oregon Inlet for its nourishment project because of the significant variation in sediment texture (Nags Head, 2011). Accumulation chemicals and hazardous substances in sand deposits also raise public health concerns if used for beach nourishment (Berry, 2009). Depletion of sand reserves raises serious concern in coastal economies like Miami, FL that depend on coastal tourism and are exploring the feasibility of importing sand from international sources such as the Bahamas (Alvarez, 2013).

A systematic increase in the cost of nourishment sand over time reflects the scarcity of sand resources and increasing demand for shoreline management (Figure 3).

The coastal economics literature largely focuses on estimating the value of beach amenities and evaluating the impact of coastal adaptation policies. Real estate markets respond directly to changes in coastal resource stocks and capitalize the value of coastal amenities and risks; empirical analyses have consistently shown that wider beaches, better beach views, lower flood risks, and proximity to waterfront increase coastal property values (Bin, et al., 2008, Bin and Polasky, 2004, Brown and Pollakowski, 1977, Gopalakrishnan, et al., 2011). Because coastal housing markets, at least partly, capitalize the impact of adaptation policies, quasi-experimental analyses using difference-in-differences approach can measure the value and potential spillover effects of investments in natural capital such as beach nourishment (Qiu and Gopalakrishnan, 2016) and the construction of dunes (Dundas, 2014).

The direct and indirect costs of coastal adaptation and the factors that affect the rate of extraction of sand reserves are, however, less understood. Alongshore towns that face similar physical environments pursue heterogeneous management strategies. For example, Carolina Beach in North Carolina implements a nourishment project approximately every three or fewer years, whereas beach nourishment intervals for communities on the Absecon Island, New Jersey are less systematic and more scattered. Examining the factors that determine the frequency of beach nourishment and the supply of beach amenities can provide insights to inform policies that efficiently allocate and price scarce sand resources. Empirical analyses looking into whether sand constraint influences beach nourishment can help us better understand the decision of beach nourishment.

Survival analyses are used to examine the duration until the occurrence of an event, such as the length of unemployment spells, the years in teaching for teachers, and the time to "IPO" for venture-backed firms (Giot and Schwienbacher, 2007, Moffitt, 1985, Singer and Willett, 1993). In environmental economics, duration models have been used to analyze firms' adoption of international standards of environmental management (Nishitani, 2009), the influences of the interaction between neighboring agents and land use externalities, and implicit regulatory costs on land development (Irwin and Bockstael, 2002, Irwin and Bockstael, 2004), the ecological and political-economic determinants of deforestation (Vance and Geoghegan, 2002), and the influence of invasive species on lakeshore housing development (Goodenberger and Klaiber, 2016).

In this paper, we use a duration model to examine the differences in nourishment patterns across coastal towns. The unit of analysis is a beach town that makes nourishment decisions. Using data from coastal towns in North Carolina and New Jersey, we examine the effect of sand access and availability on beach nourishment decisions. Demand side covariates include house price index, number of housing units, and number of beach access points with parking. Supply side drivers include distance to the closest sand reserve which may influence the costs of nourishment projects and the percentage of using renewable sand resources in previous nourishment events which indicates the availability of renewable resources. We also include some geographic covariates such as the length of shoreline and long-term erosion rate. This analysis contributes to the existing literature in several ways. First, we are among the first to empirically examine the factors influencing a beach town's decision of nourishment. Second, we test the effects of both supply and demand side drivers on the occurrence of beach nourishment.

2. Duration Analysis

Duration models are often used to analyze factors that affect the time until "an event occurs (often referred to as *failure*)". In our application this refers to the time between successive beach nourishment events. Following the framework and notation in (Greene, 2003) and (Goodenberger and Klaiber, 2016), T is a random variable with a probability density function $f(t)$ and a cumulative distribution function $F(t)$, where t is a realization of T. Define the survival function $S(t)$ as the cumulative probability that the event has not occurred by time t.

$$S(t) = Prob(T > t) = 1 - F(t) = 1 - \int_0^t f(s)ds. \tag{1}$$

Often the information of interest is the probability that the event will occur in the next time period (Δt) conditional on the fact that it has not occurred at time t. This probability, $\lambda(t)$, is called the hazard rate and can be expressed as:

$$\lambda(t) = \frac{f(t)}{S(t)} = \lim_{\Delta t \to 0} \frac{Prob(t < T \leq t + \Delta t | T > t)}{\Delta t} = \frac{1}{S(t)} \lim_{\Delta t \to 0} \frac{S(t) - S(t + \Delta t)}{\Delta t} \tag{2}$$

Parametric, semiparametric, and non-parametric hazard models can be used in duration analysis. Parametric hazard models assume a functional form of the hazard and survival functions. Semi-parametric hazard functions allow more flexibility in functional forms. In the economics literature applying duration models in analyzing land conversion decisions, researchers have generally found that parametric and semiparametric models are qualitatively similar (Goodenberger and Klaiber, 2016, Towe, et al., 2008). To examine factors that affect the implementation of a beach nourishment project, we use a Weibull hazard function because of its analytical simplicity and relevance for land use decisions.

The Weibull hazard function $\lambda(t)$ takes the following form:

$$\lambda(t) = \lambda p(\lambda t)^{p-1}. \tag{3}$$

λ is the location parameter, and p is the scale parameter that indicates acceleration or deceleration in hazard rates over time. If $p > 1$, it indicates a decrease in the expected waiting time for the event to occur. If $p < 1$, it indicates an increase in the expected waiting time for the event to occur. If $p = 1$, the model reduces to an exponential hazard model and it suggests no change in the expected duration for the event to occur. In our application to coastal adaptation, the scale parameter p allows us to test the hypothesis that beach nourishment needs to be undertaken more frequently over time because nourished beaches tend to face accelerated erosion as the shoreline returns to equilibrium (Ashton and Murray, 2006, Dean, 2002). Changes in climate forcing with sea level rise and more frequent extreme storms may also accelerate beach nourishment.

The Weibull survival function and probability density function are given by:

$$S(t) = \exp(-(\lambda t)^{p}). \tag{4}$$

$$f(t) = p\lambda^{p} t^{p-1} \exp(-(\lambda t)^{p}). \tag{5}$$

Linking the hazard function with the explanatory variables, the Weibull hazard function is:

$$\lambda_{ij} = \exp(x_{ij}'\beta), \tag{6}$$

where i represents each beach, and j represents each nourishment episode for beach i.

The log-likelihood function is then written as:

$$lnL = \sum_{\delta_{ij}=1} lnf(t_{ij}) + \sum_{\delta_{ij}=0} lnS(t_{ij}), \tag{7}$$

where $\delta_{ij} = 1$ if nourishment occurs to beach i during the time-interval t_{ij}, and $\delta_{ij} = 0$ if observation is censored and event does not occur during the interval t_{ij}. Substituting the parametric Weibull hazard and survival functions into the log-likelihood function, we have an analytical form of its log-likelihood function:

$$lnL_{Weibull}(\beta, p|t_{ij}, x_{ij}) = \sum_i \sum_j \delta_{ij}\big(p\big(lnt_{ij} - x'_{ij}\beta\big) + lnp\big) - \exp(p\big(lnt_{ij} - x'_{ij}\beta\big)). \qquad (8)$$

Because there may be multiple nourishment projects for a single beach town, we define each time-interval (t_{ij}) as the duration from the last nourishment episode to the current time period.

Duration analysis assumes that censoring of the observations does not influence the probability that an events will occur in the study period. Our analysis includes some beach towns that never implement a nourishment project during the study period 1990-2014, and are therefore right censored. For each beach town we also include each year from 1990 to 2014 so that we have a couple of observations for each town, providing more information to explain the heterogeneous nourishment frequency across space.

The data structure in the duration analysis reflects the repetitive pattern of beach nourishment decisions with multiple-event observations per beach. Because historic beach characteristics are unavailable, we restrict our analysis to the 15-year period between 1990 and 2014. We do, however, include left-censored observations of locations that have implemented beach nourishment prior to the study period. We also include the cumulative volume of sand placed on a beach through previous nourishment events as a covariate, which, at least partially, controls for the effect of historic nourishment patterns.

3. Study Area and Data

We focus on coastal towns in North Carolina and New Jersey – two states with densely developed sandy coastlines that have a long history of shoreline stabilization policy. However, beach nourishment patterns and access to sand reserves are different across the two states (Figure 4, Figure 5). The majority of sand resources in NC are near inlets or intracoastal waterways while NJ has a larger percentage of offshore sand reserves. The geographic scope of this analysis is driven primarily by availability of data on location of sand reserves and sand-source information for every beach nourishment episode. We acquired information on sand sources accessed for nourishment from the Army Corps of Engineers. We restrict the analysis to nourishment episodes that occurred after 1990 for two reasons. Data on sand access information and beach characteristics were not available for nourishment activity in prior years. Second, shoreline stabilization activity along the Atlantic coast systematically increased during the study period (Figure 1). Records maintained by Program for the Study of Developed Shoreline at West Carolina University (hereafter "PSDS") indicate that over 65% of the sand dredged for beach nourishment in the study region was placed after 1990.

The PSDS database provides information on the timing of nourishment projects, volume of sand placed and the nourishment costs for the 27 beach towns in our dataset. We calculate the cumulative volume of sand placed in previous projects events, which can partially account for the effect of nourishment in some locations prior to our study period. We include covariates that control for the cost of nourishment activity and factors that influence the demand for shoreline stabilization. A cost-side variable that is likely to influence beach nourishment is distance to the closest sand resource. We gathered spatial information of the location of sand reserves from the US Army Corps of Engineers (USACE, 2014). We use digital geospatial (GIS) information of sand reserves accessed for nourishment in New Jersey to calculate the Euclidean distance to the closest sand reserve for beaches in NJ using ArcGIS. However, such detailed spatial information is not available for North Carolina. We therefore use beach nourishment records maintained by the North Carolina Department of Environment & Natural Resource (NC DENR) and Carteret County Shore Protection Office, to identify the locations of sand reserves used for beach nourishment in North Carolina. For sand dredge sites along inlets, we identify the coordinates of inlets to geocode sand reserves and calculated the distance from a nourished beach to inlet sand source using ArcGIS. Offshore sand reserves in North Carolina are manually geocoded using maps (in pdf. Format) to measure the distance between a beach and the sand reserve.

Offshore reserves can be considered as non-renewable resources, while sand deposits from inlets and river channels are replenished on short time scales. We use an indicator variable to identify sand sources accessed for every beach nourishment event as renewable or non-renewable and constructed an intensity variable measuring the percentage use of renewable sand reserves for nourishment activities in each beach location over time. We hypothesize that beaches relying largely on renewable sand deposits along inlets or river channels are likely to nourish more frequently because of access to sustainable sand sources.

Demand for shoreline stabilization is driven by tourism and coastal amenities that are capitalized in housing markets (Qiu and Gopalakrishnan, 2016). We use geospatial information on beach attributes (NCDENR, 2013, NJDEP, 2014, USGS, 2014), to construct covariates representing beach characteristics such as shoreline length, long-term erosion rate, average elevation, and the number of beach access points with parking.

Using data on coastal housing transactions during the study period, we constructed a time-varying price index, which measures the baseline value of housing in each beach town over time.

We construct the housing price index following a strategy commonly used in the literature (Bayer, et al., 2009) and estimate the following function:

$$lnP_{i,b,t} = ln\rho_b + lnY_t + H_{i,t}\beta + \varepsilon_{i,b,t}, \tag{9}$$

where $P_{i,b,t}$ is the sale price of house i located in beach b sold in year t. It can be decomposed into a function of structural housing characteristics $H_{i,t}$, a scaling parameter ρ_b that is specific for beach town b, sale year fixed effect Y_t, and an idiosyncratic term $\varepsilon_{i,b,t}$. Equation 9 allows us to construct a price index for the value of a representative housing unit in each beach location for each year, purged of the influence of structural housing characteristics. We obtained housing transaction data from the county tax assessors' offices in North Carolina and county public records in New Jersey. We geocode the location of housing and calculated the distances to the oceanfront development line. Table A1 in the appendix shows the estimation results for the price index.

We also account for the density of housing stock in each beach location as a measure of the population that is potentially affected by nourishment decisions. Data on housing stock for each beach were collected from US census (US Census Bureau, 2016). We control for time-invariant unobservables that may influence the nourishment decisions using county-level fixed effects.

Our data set is composed of yearly observations of 13 beach towns in North Carolina and 14 beach towns in New Jersey from 1990 to 2014. We aggregate few beaches in the dataset based on close proximity, shared sand reserves and jurisdictional boundaries that result in coordinated nourishment decisions. For example, Indian Beach, Salter Path, and Pine Knoll Shores on Bogue Banks in North Carolina; Oak Island and Caswell Beach in North Carolina; Longport City, Margate City, and Ventnor City on the Absecon Island in New Jersey, and communities on the

Long Beach Island in New Jersey are aggregated into spatial units for nourishment decisions (USACE, 2014).

Beach towns that have not implemented beach nourishment prior to the start of the study period 1990 are assumed to have considered nourishment as a policy option since the year of the first beach nourishment project in the county. Table 1 shows a summary of beach nourishment activities in each beach town.

Summary statistics of explanatory variables for the duration analysis are presented in Table 2. Nourishment intervals (duration between two consecutive projects) range between 1 year (Emerald Isle, NC) and 58 years (Absecon Island, NC). The average nourishment interval is 6.05 years. On average, beach towns have approximately 30 beach access points with parking. Average elevation of oceanfront houses is 9.88 feet and beaches have an average shoreline length of 8.65 km. Average number of housing units is 5979.69. A representative beach has access to nourishment quality sand within 2.18 km and draws on a renewable source of sand from inlet deposits for about two-thirds of its nourishment projects. The average cumulative volume of sand dredged for nourishment is 4.8 million cubic yards.

4. Results and Discussion

We estimate a Weibull hazard model to examine factors that affect beach re-nourishment decisions in coastal towns and present econometric results in Table 3. A positive coefficient indicates that the covariate increases the probability of nourishment and a negative coefficient decreases the probability of nourishment (Column 1). Hazard ratios are given in Column 2. We control for geophysical features of the beach including shoreline length, average oceanfront elevation, and erosion rate. Long-run erosion rates attributable to sea-level rise and local wave climates naturally influence nourishment patterns. A one-foot per year increase in the erosion rate increases the probability of nourishment by 96%, which is intuitive considering the potential loss in recreational and other coastal amenities from losing an additional foot of beach sand. Towns with longer coastlines are more likely to nourish their beach; an additional kilometer of coastline increases the probability of nourishment by 35%. This result, while seeming less intuitive, can be explained by two factors. First, towns with longer coastlines likely support larger populations of residents and beachgoers and therefore need adaptation measures to maintain value flows. Second, nourishment records, maintained at the town level, do not identify precise spatial extents of nourishment projects. It is possible that alongshore coverage of the town boundaries may require multiple successive nourishment projects; data limitations prevent us from identifying this effect. Higher elevation of housing and development can mitigate the risks from coastal erosion. We find that a one-foot increase in the elevation of oceanfront development lowers the likelihood of nourishment by 29%.

To examine the effect of common-pool sand reserves on nourishment we consider the access to inlet sand deposits and offshore reserves. Because inlet sand deposits are effectively renewable resources, easy access to inlets can make beach nourishment more sustainable. We find that locations that depend largely on inlet deposits are much more likely to nourish their beach; when the proportion of prior nourishment events that use inlet deposits increases by 1%, the probability of re-nourishment increases by 1.5%. Farther the physical distance (in kms) to sand reserves, the less likely it is that nourishment will occur. While the direction of this influence is intuitive (towns depending on offshore sand reserves will nourish less often), the coefficient is not statistically significant. This may be because the effect of proximity to sand source is absorbed by the dependence on inlet sources. Cumulative volume of sand placed on the beach in prior years likely increases the probability of nourishment, but this estimate is also not statistically significant.

We also control for the value of housing stock that is at risk from coastal erosion. An increase in the housing stock – measured as number of single family residences – by 100 units increases the probability of nourishment by 2%. Housing price index has a large coefficient of 1.2 and is statistically significant. This suggests that locations with higher property values are much more likely to invest in beach nourishment. Our finding is consistent with the extensive empirical evidence that coastal real estate markets capitalize the value of coastal amenities (Brown and Pollakowski, 1977, Gopalakrishnan, et al., 2011, Landry and Hindsley, 2011, Pompe and Rinehart, 1995) and the benefits from investments in natural capital (beach nourishment, for example) to maintain amenity flows(Dundas, 2014, Qiu and Gopalakrishnan, 2016). We find that beach access slows down nourishment; an additional beach access point with parking space makes nourishment less likely by 7.9%. The process of beach nourishment is disruptive – it can block views, restrict ocean access, and limit recreational activity – and can therefore diminish beach value during the project implementation. Tourism-dependent locations with a high flow of beachgoers, that provide more beach access, may choose to nourish less frequently to minimize disruption. Alternatively, congestion resulting from increased beach access may decrease the value of recreational amenities, which makes nourishment less likely.

The estimated shape parameter p is 1.33 (Table 3), which implies that the hazard risk from coastal erosion increases over time. This is consistent with the geophysical processes in the coastal system that affect the rate of erosion; nourishment can accelerate erosion as a nourished beach returns to its equilibrium shoreline (Ashton and Murray, 2006, Smith, et al., 2009), and subsequently lead to more frequent nourishment.

To control for unobserved spatial heterogeneity, we include spatial fixed effects at the county level. Comparing results from Weibull hazard models with and without county fixed effects (Table 4), we find that both magnitudes and statistical significance of coefficients are different. Results suggest that time-invariant unobservables and within-county variation in physical and economic factors drive nourishment decisions.

4.1. Robustness Check

We also estimate a Cox proportional hazard model, which is a commonly used semiparametric duration model, to test for robustness of the Weibull model estimates in Table 4. In this model, the hazard function $\lambda(t)$ is assumed to be proportional to a baseline hazard function $\lambda_0(t)$:

$$\lambda(t) = \lambda_0(t)\exp(X\beta), \tag{10}$$

where X is a vector of covariates. The model allows us to recover estimates of the coefficients (β) through maximum likelihood estimation without estimating the baseline hazard $\lambda_0(t)$.

We present results from a Cox proportional hazard model in Table 5. Comparing these results with the Weibull model (Table 3), we find that both magnitudes and statistical significance of estimated coefficients are very similar across these two models. Our results are robust across parametric and semiparametric specifications.

5. Conclusion

Coastal ecosystems provide a variety of amenities and services that attract residential development and tourism. Coastal communities, that face continuous risk from rising sea levels and frequent storms, adapt by investing in shoreline stabilization to protect development. Empirical evidence suggests heterogeneous patterns across location along the U.S. Atlantic coast, but reflects an increasing number of shoreline stabilization projects via beach nourishment (Figure 1; Table 1; Gopalakrishnan, et al., 2016). When nourishment is the dominant policy, common-pool sand deposits accessed by multiple towns make localized decisions. In this paper we examine the geophysical features of the coastal-economic system, particularly the location of sand reserves, that affect beach stabilization decisions along sandy coastlines.

Our analysis shows that increased access to sand deposits from inlets and river channels, which are periodically replenished, results in more frequent nourishment. Beaches that rely on offshore reserves nourish less frequently but these projects are likely to be larger in the volume of sand placed; in North Carolina volume of sand placed in any single nourishment project is three times larger when dredged from offshore reserve relative to sand dredged from inlet sources. This is not surprising because fixed costs associated with offshore dredging – such as infrastructure and equipment – and higher than inlet dredging even when the cost of sand is not different across sources. Our finding supports earlier theoretical models of beach re-nourishment (Smith et al. 2009) and illustrates the tradeoff between fixed and variable costs of nourishment. This empirical analysis also compliments numerical models of coastline change linked with economic decisions of beach re-nourishment that show that increasing costs of sand can accelerate the depletion of a finite sand reservoir when towns with high property values are located in regions with higher erosion rates (McNamara et al. 2011).

Our analysis also reflects how physical coastline features, such as proximity to inlets, shape policy decisions. For beach nourishment to be a sustainable long-term climate adaptation policy access to renewable sand resources becomes critical. As nourishment quality sand becomes scarcer, dredging common-pool sand reserves may be inevitable. However, accounting for spillover effects, coordination nourishment decisions across both sources of sand dredged and locations where sand is placed can make beach nourishment policy more effective.

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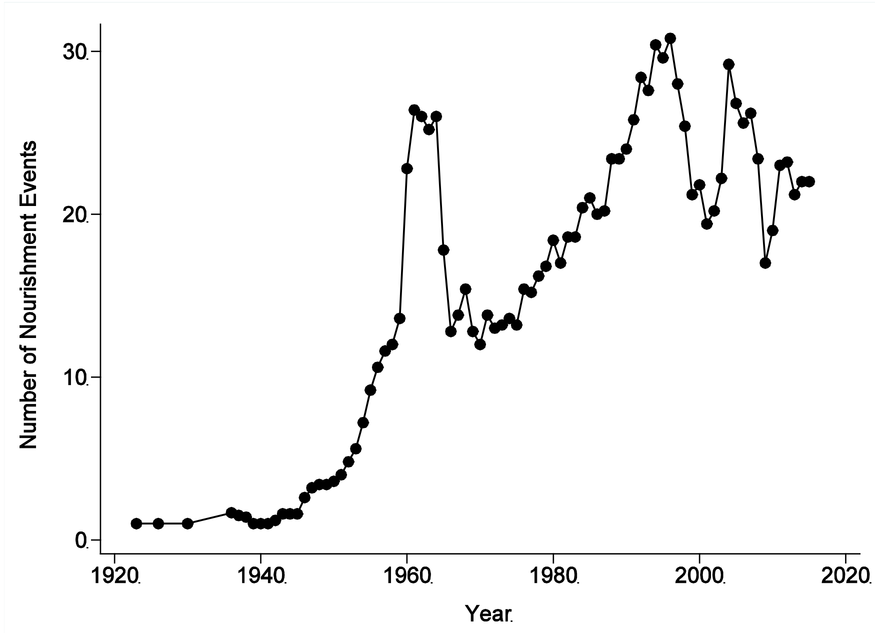

Figure 1. Yearly Number of Beach Nourishment Events (3-Year Average for US Atlantic Coast)

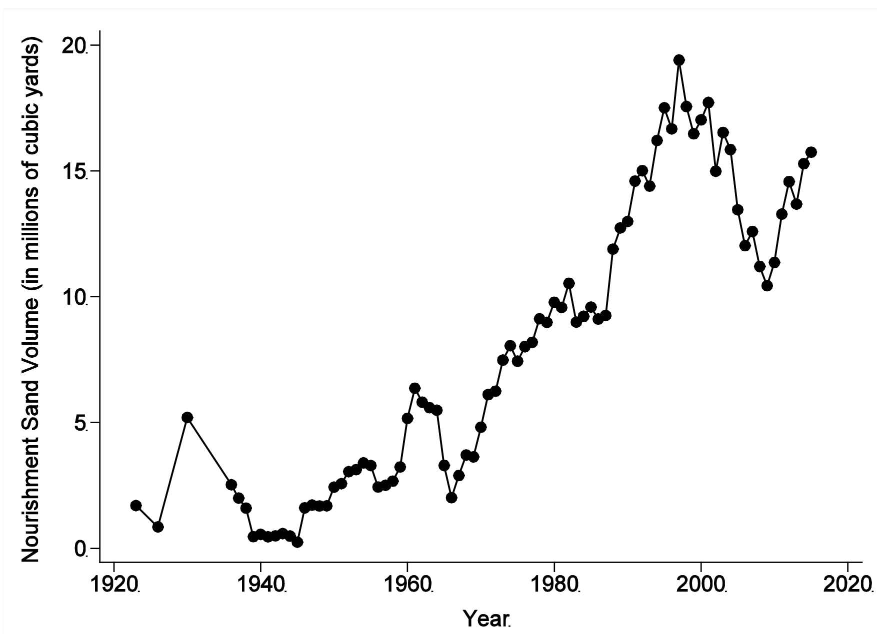

Figure 2. Yearly Volume of Sand Used for Beach Nourishment (in Cubic Yards, 3-Year Average for US Atlantic Coast)

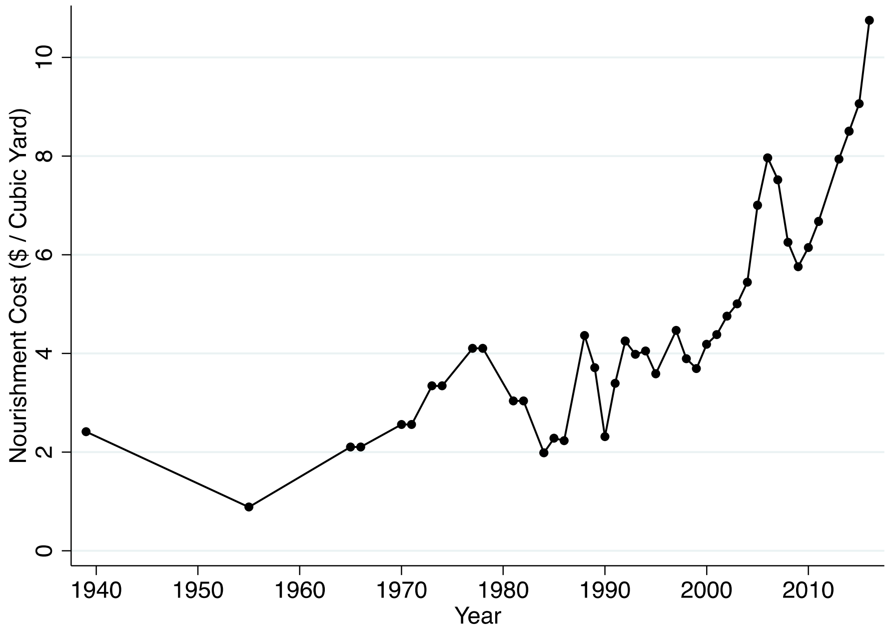

Figure 3. Nourishment Sand Costs (in 2014$) over time

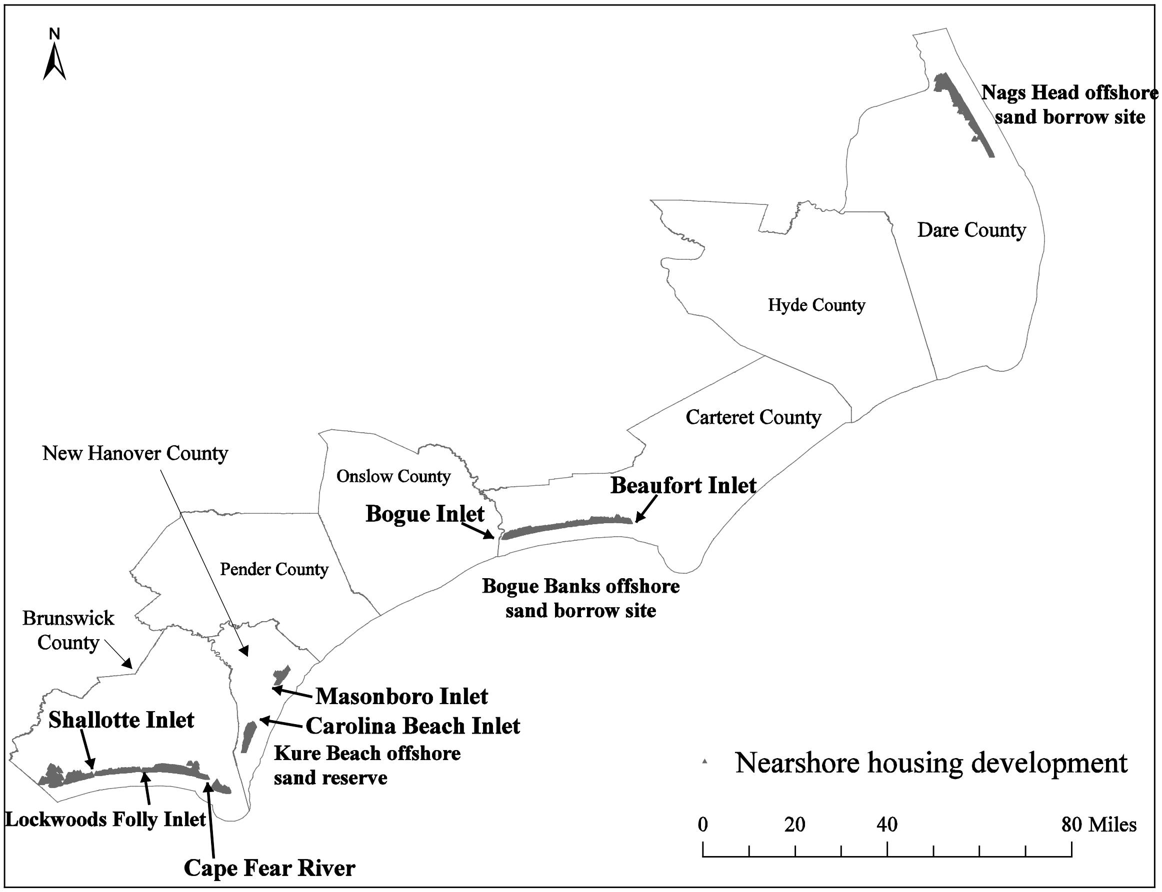

Figure 4. Sand Reserves in North Carolina

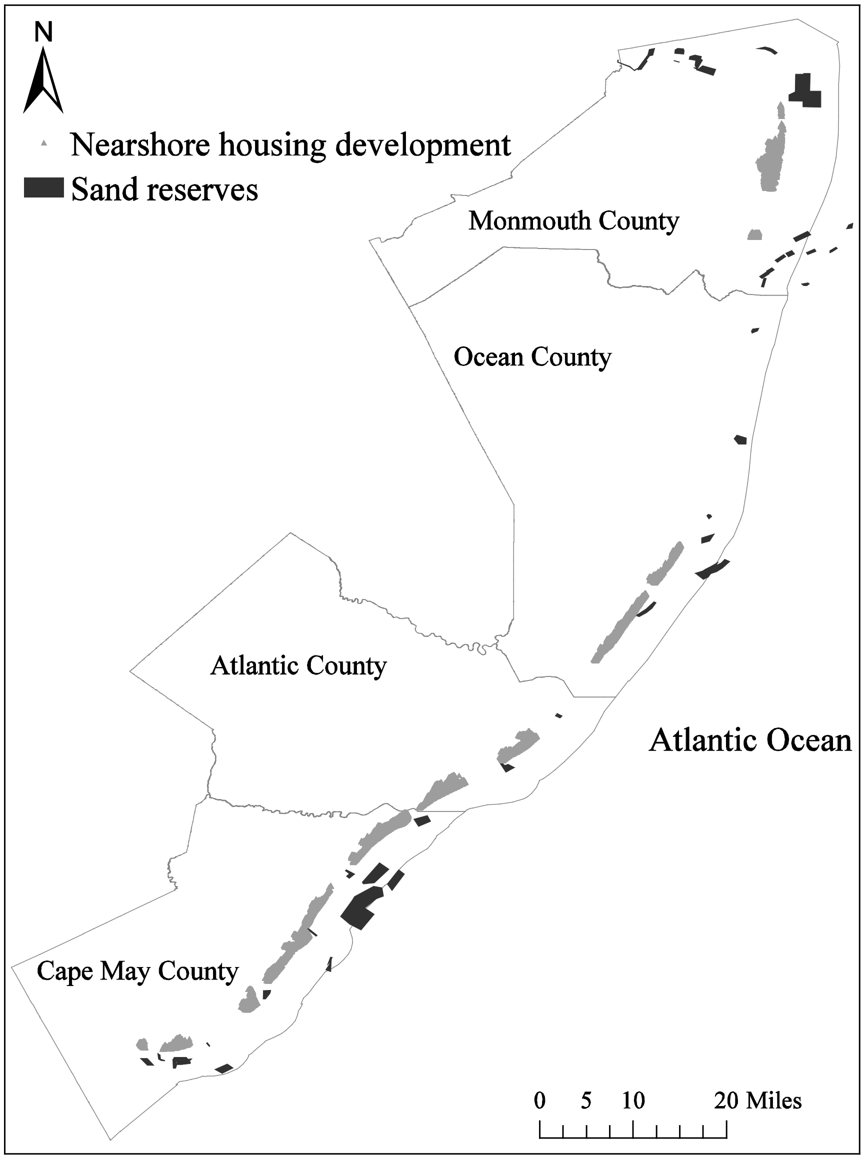

Figure 5. Sand Reserves in New Jersey

Table 1. Nourishment Activities by Beach

Beach	County	First_nourish_yr	No. of events	Average Duration (years)
Absecon Island	Atlantic	1990	17	15.60
Atlantic Beach	Carteret	1958	12	4.67
Avalon	Cape May	1962	11	3.22
Avon-by-the-Sea	Monmouth	1947	8	27.00
Bald Head Island	Brunswick	1992	10	4.20
Brigantine	Atlantic	1962	7	8.50
Cape May	Cape May	1962	20	1.79
Cape May Point	Cape May	2001	6	8.50
Carolina Beach	New Hanover	1955	28	3.00
Emerald Isle	Carteret	1984	17	1.71
Holden Beach	Brunswick	1971	22	2.89
Indian Beach/Salter Path/Pine Knoll Shores	Carteret	2002	4	13.75
Kill Devil Hills	Dare		0	
Kitty Hawk	Dare		0	
Kure Beach	New Hanover	1997	6	12.33
Long Beach Island	Ocean	1954	21	3.50
Long Branch	Monmouth	1943	8	17.00
Monmouth Beach	Monmouth	1995	3	23.00
Nags Head	Dare		1	37.00
North Wildwood	Cape May	1966	6	6.00
Oak Island/Caswell Beach	Brunswick	1986	5	6.67
Ocean City	Cape May	1952	29	2.18
Ocean Isle Beach	Brunswick	1974	12	5.00
Sea Bright	Monmouth	1963	5	10.00
Sea Isle City	Cape May	1965	9	8.33
Stone Harbor	Cape May	1967	6	11.25
Wrightsville Beach	New Hanover	1939	24	3.13

Table 2. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Duration: time between nourishment events	156	6.05	10.35	1.00	58.00
Variable	Obs	Mean	Std. Dev.	Min	Max
Number of access points w/parking	675	30.44	38.41	2.00	193.00
Shoreline length (km)	675	8.65	5.54	0.81	21.64
Elevation (feet)	675	9.88	3.52	4.00	21.00
Long-term erosion rate (feet)[a]	675	0.02	1.42	-3.53	3.96
Distance to closest sand reserve (km)	675	2.18	1.87	0.34	8.03
% Prior nourishment projects using inlet sand deposits	675	66.44	43.12	0.00	100.00
Cumulative volume of sand placed (million cubic yards)	675	4.82	5.73	0.00	27.26
Number of prior nourishment projects	675	7.48	7.28	0.00	29.00
Number of housing units	675	5979.69	5118.64	501	20871
Log price (housing)	675	12.69	0.38	12.07	13.39

[a]: Negative rate indicates accretion.

Table 3. Weibull Hazard Model

Variables	coefficients	hazard ratio
Number of access points w/parking	-0.0827***	0.9206273
	(0.0101)	
Shoreline length (km)	0.300***	1.3498588
	(0.0551)	
Elevation of oceanfront houses (feet)	-0.212***	0.8089647
	(0.0509)	
Long-term erosion rate (feet)	0.675***	1.964033
	(0.0864)	
Cumulative volume of sand placed (million cubic yards)	0.0466	1.0477028
	(0.0357)	
Distance to closest sand reserve (km)	-0.0884	0.9153946
	(0.165)	
% Prior nourishment projects using inlet sand deposits	0.0149***	1.0150116
	(0.00472)	
Number of housing units	0.000172***	1.000172
	(4.37e-05)	
Price index	1.214***	3.3669255
	(0.255)	
Dummy (Dare County)	-16.85***	
	(1.856)	
Dummy (Carteret County)	-9.774***	
	(1.350)	
Dummy (Brunswick County)	-11.02***	
	(1.674)	
Dummy (New Hanover County)	-7.518***	
	(1.435)	
Dummy (Cape May County)	-7.494***	
	(0.941)	
Dummy (Atlantic County)	-9.916***	
	(1.788)	
Dummy (Monmouth County)	-10.14***	
	(1.616)	
Constant	-8.955***	
	(3.413)	
ln(p)	0.284**	
	(0.143)	
Observations	675	

Robust standard errors clustered by beach are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4. Weibull hazard models with & without county FE

Variables	I	II
Number of access points w/parking	-0.0827***	-0.00444
	(0.0101)	(0.00773)
Shoreline length (km)	0.300***	0.113***
	(0.0551)	(0.0381)
Elevation of oceanfront houses (feet)	-0.212***	0.0573
	(0.0509)	(0.0616)
Long-term erosion rate (feet)	0.675***	0.0550
	(0.0864)	(0.197)
Cumulative volume of sand placed (million cubic yards)	0.0466	0.1300***
	(0.0357)	(0.0302)
Distance to closest sand reserve (km)	-0.0884	-0.0899
	(0.165)	(0.108)
% Prior nourishment projects using inlet sand deposits	0.0149***	0.0150
	(0.00472)	(0.0135)
Number of housing units	0.000172***	-6.06e-05
	(4.37e-05)	(5.39e-05)
Price index	1.214***	0.869***
	(0.255)	(0.231)
Dummy (Dare County)	-16.85***	
	(1.856)	
Dummy (Carteret County)	-9.774***	
	(1.350)	
Dummy (Brunswick County)	-11.02***	
	(1.674)	
Dummy (New Hanover County)	-7.518***	
	(1.435)	
Dummy (Cape May County)	-7.494***	
	(0.941)	
Dummy (Atlantic County)	-9.916***	
	(1.788)	
Dummy (Monmouth County)	-10.14***	
	(1.616)	
Constant	-8.955***	-16.06***
	(3.413)	(3.813)
ln(p)	0.284**	0.0659
	(0.143)	(0.212)
Log pseudo likelihood	-379.02616	-456.0665
Observations	675	675

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5. Cox Proportional Hazard Model

Variables	coefficients
Number of access points w/parking	-0.0734***
	(0.00788)
Shoreline length (km)	0.248***
	(0.0414)
Elevation of oceanfront houses (feet)	-0.154***
	(0.0308)
Long-term erosion rate (feet)	0.593***
	(0.0990)
Cumulative volume of sand placed (million cubic yards)	0.0165
	(0.0367)
Distance to closest sand reserve (km)	-0.119
	(0.153)
% Prior nourishment projects using inlet sand deposits	0.0143***
	(0.00421)
Number of housing units	0.000155***
	(4.95e-05)
Price index	1.094***
	(0.229)
Dummy (Dare County)	-14.49***
	(1.233)
Dummy (Carteret County)	-9.111***
	(1.156)
Dummy (Brunswick County)	-10.08***
	(1.289)
Dummy (New Hanover County)	-7.071***
	(1.307)
Dummy (Cape May County)	-6.752***
	(0.738)
Dummy (Atlantic County)	-8.813***
	(1.375)
Dummy (Monmouth County)	-9.332***
	(1.386)
Log pseudo likelihood	-787.99389
Observations	675

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix

Table A1. Hedonic Regression for North Carolina and New Jersey Coastal Towns

Variables	log_price
Sqft	0.00102***
	(1.08e-05)
Square of sqft	-1.38e-07***
	(2.95e-09)
Property's age	-0.00145***
	(0.000218)
Square of property's age	-8.51e-06***
	(2.27e-06)
Single family dummy	0.0306***
	(0.00718)
Distance to oceanfront (m)	-0.000245***
	(4.22e-06)
Constant	10.51***
	(0.0278)
Beach FE	Yes
Year FE	Yes
Observations	80,759
R-squared	0.699

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.