Environment and Natural Resources Program

What are the Welfare Costs of Shoreline Loss?

Housing Market Evidence from a Discontinuity Matching Design

By Matthew Ranson

HARVARD Kennedy School
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ABSTRACT

This paper uses housing market data to estimate the welfare costs of shoreline loss along coastal beaches in Florida. I develop a forward-looking structural model of a housing market in which a time-variant housing characteristic (beach width) follows a Markov process. I use this model to provide an exact welfare interpretation for the coefficients from three empirical research designs: (1) a repeat-sales panel regression of housing prices on beach width; (2) a differences-in-differences approach based on sharp changes in beach width caused by beach nourishment projects; and (3) a new "discontinuity matching" research design that exploits capitalized housing price differentials created by predictable changes in future beach width. Using a unique panel dataset on housing sales, beach width survey measurements, and the timing of 204 beach nourishment projects along 300 miles of Florida's coastline, I then use each of these research designs to estimate homeowners' willingness to pay for an extra foot of sand. In contrast to previous work, I find that changes in beach width have little impact on housing prices, except possibly at very eroded beaches. The results imply that the welfare costs of sea level rise may be low up to a threshold, and then increase sharply.

Key words: hedonic models, climate change, shoreline loss, sea level rise, matching

JEL Classification: Q51, R0, C14

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1 Introduction

Many sections of the U.S. coastline are severely eroding. The average long-term rate of shoreline loss along the New England and mid-Atlantic coasts is 1.6 feet per year, with much higher rates in areas such as southern Nantucket Island in Massachusetts (12 feet per year) and the southern portion of the Delmarva Penninsula in Maryland (9.5 feet per year) (Hapke et al, 2010; Woods Hole, 2000). In Florida, some segments of beach lose as much as ten to twenty feet per year (FDEP, 2000, 2001). Under current predictions of a 1.1 foot rise in average sea levels by the year 2100, these erosion rates will accelerate, and between 3,000 and 7,000 square miles of dry land could be lost (IPCC, 2007; Titus, 1989). Although it is possible to protect coastal areas from shoreline loss—through installation of hardened features such as seawalls and groins, imposing set-back and minimum-height home construction requirements, and performing periodic nourishments to place new sand onto eroded beaches—the costs are substantial. For example, the Florida Department of Environmental Protection projects that 1.1 billion dollars would be needed between 2011 and 2015 for full implementation of the state's strategic beach management plan.

Surprisingly, given both the substantial costs of preventing coastal erosion and the serious risks posed by retreating shorelines and rising sea levels, there is little rigorous evidence on the benefits of wider beaches for coastal property owners. Existing studies suggest that the sale price of a coastal home increases between 70 dollars and 8,000 dollars per one foot increase in beach width (Gopalakrishnan et al, 2010; Landry, Keeler, and Kriesel, 2003; Pompe and Rinehart, 1995). However, since cross-sectional hedonic property value regressions suffer from well-known theoretical and econometric problems, the interpretion of these estimates is not clear. Coefficients from hedonic regressions are biased when one of the housing attributes (such as beach width) varies over time (Abelson and Markandya, 1985). Furthermore, cross-sectional hedonic regressions are vulnerable to problems with omitted variable bias (Chay and Greenstone, 2005; Kuminoff, Parmeter, and Pope, 2010)—as might be the case if higher quality houses are built along wider sections of beach.

In this paper, I estimate the welfare costs of shoreline loss along coastal beaches in Florida, using three distinct research designs that each solve both of the theoretical and econometric problems discussed above. These research designs are: (1) a repeat-sales regression of housing prices on beach width that controls for fixed housing characteristics and aggregate housing market shocks; (2) a differences-in-differences approach based on the sharp and substantial discontinuity in beach width caused by beach nourishment projects; and (3) a new "discontinuity matching" approach that exploits capitalized housing price differentials created by government policies that result in predictable changes in future beach width. In all three approaches, I take seriously the problem of giving a theoretical interpretation to the estimated coefficients.

The paper makes three main contributions. First, using the empirical approaches discussed above, I develop the first panel data estimates of homeowners' marginal willingness to pay to avoid coastal shoreline loss. My analysis is based on a unique dataset that includes 1.1 million housing sales transactions at parcels located within five kilometers of a coastal beach in sixteen Florida counties between 1983 and 2009 (the dataset includes 388 miles of coastline). I link these data to high-resolution beach width survey records at fixed monuments located approximately 1000 feet apart along the Florida coastline. Finally, I add information about the timing, location, and volume of sand for 204 beach nourishment projects. This list represents the most detailed dataset of Florida nourishment projects ever compiled.

Second, I develop a "Rosen-like" structural housing market model that provides an intuitive interpretation for the coefficients from hedonic regressions of housing prices on a time-varying neighborhood characteristic (such as beach width). When homebuyers have rational expectations and changes in the characteristic are Markovian, the model equilibrium implies that the cross-sectional relationship between housing prices and characteristics has an exact interpretion as willingness to pay for a policy intervention that increases current amenity quality by one unit and then allows it to evolve in an unconstrained way in future periods (e.g., willingness to pay for a one-time beach nourishment project). Unlike previous work, which has treated the coefficients from panel hedonic regressions as biased estimates of marginal willingess to pay for a *permanent* increase in amenity quality (Abelson and Markandya, 1985; DiPasquale and Wheaton, 1994; Bayer, McMillan, Murphy, and Timmins, 2008; Bishop and Murphy, 2011), I argue that it is much more accurate—and useful—to interpret these coefficients as willingness to pay for a *one-time* marginal policy intervention (such as beach nourishment).

The paper's third contribution is to develop a new "discontinuity matching" research design that recovers consumers' marginal willingness to pay by exploiting capitalized housing price differentials caused by construction projects that result in predictable changes in future amenity quality. Recent empirical work on hedonic models has considered several sources of identifying variation in amenity quality, including unexpected shocks (Davis, 2004; Greenstone and Gallagher, 2008; Kuminoff and Pope, 2010a,b) and cross-sectional discontinuities resulting from arbitrary geographic boundaries such as school district borders (Black, 1999). In contrast, my discontinuity matching approach exploits the change in capitalized housing prices that accompanies *predictable* discontinuities in amenity quality. Typically, these discontinuities will be the result of a policy intervention, e.g., beach nourishment, construction of a new school, or completion of a public transportation project. For example, suppose that two otherwise-similar houses are located on two different beaches, one of which—by random chance—is heavily eroded this year. If the government announces that the eroded beach will be nourished next year, then prospective homebuyers would rationally expect the two beaches to have similar width next year (and in all future periods). Thus, a comparison of current prices and current beach width across these two houses will reveal the marginal rental value of living on a wider beach for one year.

The paper establishes several empirical results. First, using semi-parametric panel regressions, I find that beach width has only a modest effect on housing prices. According to these regressions, the difference in sales price between a house with a 200 foot wide beach and a house with 50 feet of beach is only about 2.1 percent. However, houses with less than 20 feet of beach do experience a suggestive—but only marginally significant—price discount of 6 to 14 percent. Second, my differences-in-differences regressions show beach nourishment adds a statistically significant 83 feet to the width of the average beach. However, housing prices only gain an insignificant 1.2 percent between two years before and after nourishment, and I can reject the possiblity that housing prices increase by more than 4.9 percent during this period. Finally, using the discontinuity matching approach, I estimate that the yearly rental value of an extra foot of beach is approximately $29 per household, and not statistically different from zero. Overall, the results imply that the welfare costs of sea level rise may be low up to a threshold, and then increase sharply.

This paper builds on a growing literature on the microfoundations of hedonic models (Rosen, 1974; Roback, 1982; Bajari and Benkard, 2005; Bishop and Timmins, 2008a,b; Kuminoff and

Jarrah, 2010). A few studies have cast housing choice as a dynamic utility maximization problem (DiPasquale and Wheaton, 1994; Bayer, McMillan, Murphy, and Timmins, 2008; Bishop and Murphy, 2011) or as a dynamic process with slow adjustment (Riddel, 2001; Mankiw and Weil, 1989), or have modeled neighborhood amenities as dynamic processes (McCluskey and Rausser, 2001). Others have developed methodologies for using panel data to identify hedonic regressions, either using new discrete choice methods (Bajari et al, 2010; Kuethe, Foster, and Florax, 2008) or a repeat sales methodology employing first-differencing or fixed effects (Palmquist, 1982; Mendelsohn et al, 1992). However, to the best of my knowledge, there are no hedonic studies that attempt to estimate rental prices by decomposing sales prices into current and future rental components. Although authors do recognize that the price on the left side of a hedonic equation should interpreted as a discounted sum of rental prices (Dougherty and Van Order, 1982; Abelson and Markandya, 1985; Blackley and Follain, 1996; Meese and Wallace, 2003; Bajari and Kahn, 2007; Diewert, Nakamura, and Nakamura, 2009), in practice, most studies use a "static-equivalent" rental price calculated by multiplying the sales price by the discount rate (Bajari and Kahn, 2005; Gyourko and Tracy, 1991; Bishop and Murphy, 2011). The paper is also related to more macro-oriented literatures on housing markets, for example, literatures on calculating price indices and implicit rents for owner-occupied housing (Case and Schiller, 1989; Rondinelli and Veronese, 2011), evaluating the relationship between rental prices and sales prices (Gallin, 2004), and assessing the welfare impacts of changes in housing prices (Bajari, Benkard, and Krainer, 2005).

The remainder of this paper is organized as follows. Section 2 provides background on coastal shoreline retreat and beach nourishment. Section 3 describes a structural model of a housing market and demonstrates how it can be used to calculate willingness to pay for wider beaches. Section 4 describes my dataset and presents summary statistics. Section 5 explains the details of my econometric approach, and Section 6 presents my main empirical results. Section 7 discusses the results, and Section 8 concludes.

2 Background

The United States has more than 12,000 miles of coastline, of which a significant portion consists of sandy beaches (NationalAtlas.gov, 2011). Unlike dry land, coastal beaches are highly dynamic physical environments that experience significant seasonal and yearly changes. For example, many beaches erode during the winter, due to heavy waves, and then accrete during milder summer weather. Over longer time horizons, beaches exhibit a variety of erosional patterns that depend on natural factors such as the underwater coastal profile, dominant wave and weather patterns, and major storm events (NRC, 1995).

Because proximity to the coast provides a variety of benefits, the land along many beaches is heavily developed. Unfortunately, historical development patterns in many areas have failed to anticipate the degree to which erosion can reshape the coastline. Furthermore, some types of development, such as the dredging of coastal waterways and inlets, have constributed substantially to erosion problems. Thus, many properties that once looked out over wide coastal beaches now face serious problems with shoreline loss.

Policy responses to shoreline loss take several main forms (NRC, 1995). The first is the construction of hardened features, such as seawalls and jetties, that are intended to protect buildings and prevent sand from moving along the coast. Although these features can succeed in trapping pockets of sand, they sometimes have the perverse result of creating leeward hotspots in which erosion patterns are magnified. A second policy option is establishing legal permitting requirements that require new houses to be set back some specified distance from the beach. While this approach is workable in undeveloped areas, it has the obvious drawback of failing to address erosion problems at existing homes. A third option is abandonment and retreat. This is considered an option of last resort.

One final policy response to coastal erosion along sandy beaches is beach nourishment. In a typical nourishment project, sand from an offshore borrow area is pumped or dredged onto a beach to make it wider (NRC, 1995). Because the volume of sand required for nourishment projects is quite large—as high as several million tons—locating suitable sources of sand is a major challenge for these projects. Furthermore, the process is expensive: nourishment costs approximately one million dollars per mile of beach (USACE, 1996). Because of this high cost, localities often obtain state and federal funding for nourishment projects. For example, between 1950 and 1993, the U.S. Army Corps conducted 56 large beach nourishment projects that covered a total of 210 miles of U.S. shoreline. The cumulative federal cost share for these projects was $881 million dollars (USACE, 1996). The NOAA Coastal Resources Center (2009) reports that federal, state, and local organizations have spent at least $2.5 billion dollars on 242 major beach nourishment projects since 1950.

Although the costs of policy responses such as beach nourishment are not difficult to calculate, the benefits of these policies are less clear. The central question is: what is the value of widening a particular section of beach? This question is complicated by the fact that beaches provide a variety of economic benefits to local communities, including recreational opportunities, scenic views, protection from coastal storms, and tourism revenues.

In this paper, I focus on estimating only one component of the economic contribution of beaches: the welfare benefits to beachfront homeowners. Although there are many reasons why beaches may be valuable, their contribution to the welfare of local residents is likely to be one of the most important. Furthermore, by focusing on the economic benefits to homeowners, I am able to use a hedonic property value approach that exploits the relationship between housing prices and beach quality (Rosen, 1974).

There is a small existing literature that uses such hedonic techniques to estimate the benefits of wider beaches to local homeowners. To the best of my knowledge, all of this previous work focuses on the cross-sectional relationship between beach width and housing prices.[1] The most recent of these studies is Gopalakrishnan et al (2010), who use distance from the continental shelf and beach attributes such as scarps as instruments for beach width.[2] They find that in a cross-section of coastal properties in ten North Carolina towns, a one-foot increase in beach width is associated with a 1.1 percent increase in property values (about $8,800). Although their empirical strategy does control for the potential endogeneity of beach nourishment decisions, it does not

[1]There has also been theoretical work on beach nourishment. Most notably, Smith et al (2009) discuss beach nourishment as an example of a dynamic capital accumulation problem. They show that nourishment frequency depends on whether sand erodes at a rate greater or less than the discount rate.

[2]Other than Gopalakrishnan et al (2010), I am aware of no other studies of the benefits of beach width that use quasi-experimental methods.

address the possibility that higher-quality houses are more likely to be built on wider beaches.

This cross-sectional literature also includes a variety of earlier studies. For example, Landry, Keeler, and Kriesel (2003) estimate the benefits of beach nourishment for Tybee Island, Georgia, using the cross-sectional relationship between beach width and property values, for 318 properties sold between 1990 and 1997. They find that a one meter increase in beach width increases property values by $213. Using similar techniques, Pompe and Rinehart (1995) find that increasing beach width by one foot increases beachfront property values by $558 to $754 in the Grand Strand area of North Carolina. Properties half a mile inland also benefit by $165 to $254. Other authors have also used hedonic techniques to evaluate the benefits of beach nourishment, but their empirical strategies are less rigorous. For example, Edwards and Gable (1991) use a hedonic model to estimate the value of proximity to a beach in South Kingstown, Rhode Island, and then calculate the benefits of beach nourishment by assuming that nourishment prevents beaches from becoming unusable. Parsons and Powell (2001) use a similar methodology to evaluate the benefits of beach nourishment in Delaware. Woglom (2003) develops a simulation model of beach nourishment, using parameter estimates from earlier studies.

Additionally, a few related studies estimate the value of proximity to the coastline, but do not directly analyze beach width. For example, Milon, Gressel, and Mulkey (1984) use cross-sectional regressions to estimate how the value of a home depends on its distance from the mean high water (MHW) mark, for homes in Apalachicola Bay, Florida. Other similar studies include Bin et al (2008), Parsons and Wu (1991), and Brown and Pollakowski (1977). Kriesel, Randal, and Lichtkoppler (1993) consider the value of erosion protection in the Great Lakes. Bell and Leeworthy (1990) and Bin et al (2005) use a travel cost approach to estimate the recreational benefits of beach days, but do not consider the impact of beach width on willingness to pay.

As discussed in the introduction, the interpretation of estimates from this existing body of work faces several challenges, given potential theoretical and empirical problems. When neighborhood attributes (such as beach width) vary over time, a regression of housing prices on the time-variant attribute does not identify true marginal willingness to pay for a permanent increase in attribute quality (Abelson and Markandya, 1985). Furthermore, since cross-sectional hedonic regressions are vulnerable to problems with omitted variable bias (Chay and Greenstone, 2005; Kuminoff, Parmeter, and Pope, 2010), it is entirely possible that previous work has found a positive relationship between housing prices and beach width because higher quality houses are built along wider sections of beach. Thus, I devote the remainder of this paper to developing several research designs for estimating homeowners' willingness to pay for wider beaches that solve both the theoretical and econometric issues in previous work.

3 Theory

3.1 Hedonic Model

In this section, I develop a simple structural model of a housing market, based on Rosen (1974), that explicitly considers the time dimension of housing choice. The model has two purposes. First, it provides a welfare interpretation for the coefficients from panel hedonic regressions of housing prices on time-varying neighborhood characteristics. Second, the model suggests a new "discontinuity matching" research design that can be used to recover homeowners' implied valuations of neighborhood characteristics. This procedure exploits capitalized housing price differentials caused by policy interventions that lead to predictable improvements in future neighborhood amenity quality (e.g., interventions such as beach nourishment, construction of a new school, or completion of a public transportation project).

The model differs from other recent multi-period hedonic models (DiPasquale and Wheaton, 1994; Bayer, McMillan, Murphy, and Timmins, 2008; Bishop and Murphy, 2011) in several ways. First, my model is not dynamic, in the sense that all choices are made in the first period, with no possibility of re-optimization or sorting in future periods. However, because these initial choices do reflect consumers' expectations about how housing characteristics will change in the future, the model still allows for an "as-if" dynamics that captures much of the intuition and theoretical content of a fully-dynamic model. Second, the model excludes transaction costs. Although real-estate fees and moving costs do contribute substantially to the cost of purchasing a house, inclusion of these transaction costs would complicate the model without changing its fundamental conclusions. Third, consumers in my model have advance knowledge about policy interventions that improve the quality of neighborhood characteristics. This stands in contrast to other recent work, in which policy interventions are modeled as unpredictable shocks (Davis, 2004; Greenstone and Gallagher, 2008; Kuminoff and Pope, 2010a,b).

The model is as follows. Suppose that there are many heterogeneous consumers, indexed $1, ..., j, ..., J$, each of whom has preferences θ_j and receives fixed income $\bar{y}_j$ each period. Both θ_j and $\bar{y}_j$ can vary across individuals, but are constant over time. There are also many houses, indexed $1, ..., i, ..., I$, each of which has a time-invariant characteristic π_i that represents permanent housing quality (e.g., a composite index measuring the number of bedrooms, square footage, and ceiling height) and a time-variant characteristic w_{it}. Although w_{it} could represent any housing or neighborhood amenity that changes over time, for expositional purposes, suppose that all houses are located on the coast, and that w_{it} measures the width of beach between house i and the high-tide mark. The evolution of w_{it} over time (due to erosion and accretion of sand) is described by the following assumption:

Assumption 1. ***Markov Amenity Quality:*** *The time-variant amenity w_{it} follows a Markov process. Furthermore, all houses share the same Markov transition probabilities for amenity quality, given by the transition function $T(w', w)$:*

$$\Pr(w_{i,t+1} = w' | w_{it} = w) = T(w', w) \tag{1}$$

Immediately before period 1 begins, each consumer takes out a loan, based on her future income, and uses the loaned money to purchase a house at the market price $p(w_1, \pi)$. The model timing is such that at the time the consumer purchases a house, she knows with certainty the amenity value in period 1 and has rational expectations about the amenity values in period 2 onwards. Let r be the competitive interest rate. Then, each period, the consumer pays the mortgage payment $r \cdot p(w_1, \pi)$ and uses her remaining income that period to purchase c units of a "composite" good with unit price 1, where the composite good represents a mixture of any other goods and services that the consumer finds desirable: food, entertainment, transportation, etc. The consumer's utility from consuming c units of the composite good and owning a house with current characteristics w and π for one time period is given by $u(w, \pi, c; \theta_j)$. The shared pure rate of time preference is ρ.

Let Γ represent the set of combinations of characteristics $\{(w_{1,1}, \pi_1), ..., (w_{i1}, \pi_i), ..., (w_{I1}, \pi_I)\}$ of all houses in period 1. For analytical convenience, I formulate each consumer's maximization problem as a choice of characteristics, rather than as a choice of discrete houses. In other words, rather than choosing a house i from the set of available houses $\{1, ..., I\}$, each consumer chooses a combination of characteristics (w_1, π) from the set of available characteristics Γ. Thus, dropping the subscripts i that index houses, consumer j's maximization problem is:

$$\max_{(w_1,\pi), c\in\{\Gamma,\Re_+\}} E\left[\sum_{t=1}^{\infty}\left(\frac{1}{1+\rho}\right)^t u(w_t, \pi, c; \theta_j)\right] \tag{2}$$
$$s.t. \qquad \begin{cases} \sum_{t=1}^{\infty}\left(\frac{1}{1+r}\right)^t \bar{y}_j \geq p(w_1, \pi) + \sum_{t=1}^{\infty}\left(\frac{1}{1+r}\right)^t c \\ \Pr(w_{t+1} = w' | w_t = w) = T(w', w) \end{cases}$$

Equation (2) is a straightfoward expected utility maximization problem. The consumer chooses beach width, permanent housing quality, and the composite good in such a way as to maximize the expectation of the present discounted flow of future utility, while still satisfying the intertemporal budget constraint that the present discounted sum of future income must be greater than or equal to the price of the selected house plus the present discounted sum of future expenditures on the composite good. Note here the analytical value of Assumption 1. Even though consumers are forward-looking, the "memorylessness" property of Markov processes allows the price of house i to be represented as a function of only two variables: w_{i1} and π_i. In the beach width example, the assumption implies that once a prospective homebuyer observes the current width of the beach in front of house i, information about beach width in previous periods provides no additional information about whether the beach is likely to erode or accrete in the future. Thus, Assumption 1 collapses a vector of past and current measurements and future beliefs about beach width into a single metric: current beach width. This greatly simplifies the formulation and solution of the consumer's choice problem.

Under some mild regularity conditions (e.g., that the market is sufficiently thick that there is no need to consider corner solutions caused by gaps in the continuum of housing characterics), the solution to (2) is characterized by the following first-order conditions:

$$\frac{\partial}{\partial w_1} E\left[\sum_{t=1}^{\infty}\left(\frac{1}{1+\rho}\right)^t u\Big(w_t, \pi, \bar{y}_j - rp(w_1, \pi); \theta_j\Big)\right] = 0 \tag{3}$$

$$\frac{\partial}{\partial \pi} E\left[\sum_{t=1}^{\infty}\left(\frac{1}{1+\rho}\right)^t u\Big(w_t, \pi, \bar{y}_j - rp(w_1, \pi); \theta_j\Big)\right] = 0 \tag{4}$$

Let u_j represent the utility function for consumer j with preferences θ_j. Interchanging the order of the differentiation and expectation operators in Equation (3) leads to the following result:

Theorem 1. ***Welfare Interpretation of Panel Hedonic Regressions:*** *Suppose that in equilibrium, consumer j purchases house i. Consider a counterfactual marginal policy intervention that would increase the initial (period 1) quality of the time-varying amenity w_{i1} at house i by one unit, and then allow it to evolve freely in future periods according to the Markov process described in Assumption 1. Consumer j's willingness to pay for this intervention is given by the derivative of equilibrium housing prices with respect to current amenity quality:*

$$\frac{\partial p}{\partial w_1}\Big|_{w_{i1}} = \frac{\sum_{t=1}^{\infty}\left(\frac{1}{1+\rho}\right)^t E\left[\frac{\partial u_j}{\partial w}\Big|_{w_t}\frac{\partial w_t}{\partial w_1}\Big|_{w_{i1}}\right]}{\sum_{t=1}^{\infty}\left(\frac{1}{1+\rho}\right)^t E\left[r\frac{\partial u_j}{\partial c}\Big|_{w_t}\right]} \tag{5}$$

This theorem, which generalizes Rosen's (1974) result, provides a welfare interpretation for the empirical relationship between housing prices and amenity quality.[3] The left-hand side of Equation (5) is the derivative of housing price with respect to the time-varying amenity (e.g., beach width). This derivative can be directly estimated as the coefficient from a regression of housing prices on beach width. The right-hand side of Equation (5) represents consumer j's willingness to pay—by giving up some of the composite good each time period—to achieve the increase in expected utility caused by starting at an initial amenity level that is one unit higher. Thus, unlike

[3] In his seminal 1974 paper, Rosen develops a one-period housing market model in which heterogeneous consumers purchase houses of different quality. He argues that in this static equilibrium, the relationship between price and amenity quality reflects the marginal consumer's willingness to pay for a marginal increase in the amenity. In my notation, his conclusion can be written as: $\frac{\partial p}{\partial w} = \frac{\partial u_j}{\partial w} / \frac{\partial u_j}{\partial c}$. However, because his model has only one period, it is not applicable to situations in which w varies over time.

Rosen's original theorem, which interprets the relationship between housing prices and amenity quality as willingness to pay for a permanent one-unit increase in amenity quality, Equation (5) expresses willingness to pay for a policy intervention that increases initial amenity quality by one unit and then allows it to evolve in an unconstrained way in future periods, according to the Markov transition function specified in Assumption 1.

The value of Theorem 1 is that it provides an exact welfare interpretation for the coefficients from hedonic regressions with time-varying characteristics. It is well known from previous work that panel regressions produce biased estimates of marginal willingess to pay for a permanent increase in amenity quality (Abelson and Markandya, 1985; DiPasquale and Wheaton, 1994; Bayer, McMillan, Murphy, and Timmins, 2008; Bishop and Murphy, 2011). However, when the time-varying characteristic follows a Markov process, Theorem 1 provides a useful economic interpretation for such regressions. For example, in the context of this paper, Theorem 1 implies that the coefficient from a regression of housing prices on beach width can be interpreted as homeowners' willingness to pay for a one-time beach nourishment project that widens the beach by one foot in the current year.

3.2 Discontinuity Matching Research Design

Theorem 1 provides a valuable interpretation for the relationship between observed housing prices and consumers' preferences. However, in many circumstances, it is desirable to know consumers' exact marginal willingness to pay for a *permanent* increase in amenity quality. Thus, in this section, I use the structural housing model from the previous section to motivate a new "discontinuity-matching" research design that can be used to estimate consumers' marginal willingness to pay for a guaranteed, immediate, one-period, one-unit increase in amenity quality. This estimate can be then scaled, using the discount rate, to generate an estimate of MWTP for a permanent increase in amenity quality.

The core idea of the discontinuity matching design is to exploit capitalized housing price differentials caused by predictable discontinuities in future neighborhood amenity quality. Typically, these discontinuities will be the result of a policy intervention, e.g., beach nourishment, construction of a new school, or completion of a public transportation project. Because the price of a house reflects the capitalized value of the future flow of utility from owning that house, predictable improvements in future amenity quality will be reflected in current prices. Thus, current price differences—between matched sets of houses that are expected to have similar post-intervention (post-discontinuity) amenity values—reflect only current differences in amenity quality.

For additional intuition, consider the following example. Imagine two otherwise-identical houses located on two different sections of beach. Suppose that both beaches have similar rates of erosion, but that due to random fluctuations, one of the beaches is heavily eroded this year, and the other is not. Now, suppose that the government announces that next year, the heavily eroded section of beach will be nourished. As a result, potential homebuyers believe that the two sections of beach will be approximately the same width next year. Because the houses located on these beaches are otherwise identical, and because homebuyers have identical expectations about the widths of the beaches in year 2 and onwards, any difference in the current-year sales price of the two houses must be attributable to the current difference in beach width. Thus, after controlling for consumers' beliefs about beach width next year, the relationship between current housing prices and current beach width has an exact interpretation as the marginal rental value of an extra year of improved beach width.

To prove a formal version of this argument, I use the structural housing model from the previous section to model the consequences of a policy intervention that causes a predictable future discontinuity in amenity quality. As before, at the start of period 1, amenity quality w_{i1} at each house is given. However, between periods 1 and 2, a policy intervention equalizes amenity quality across all houses (or at least, equalizes the probability distribution of amenity quality), regardless of each house's period 1 quality. Then, in period 3 and all following periods, the amenity at each house evolves as a Markov process.

A more formal statement of this assumption is as follows:

Assumption 2. ***Period 2 State Is Independent of Period 1 State:*** *In period 1, amenity quality w_{i1} at each house i is given. In period 2, amenity quality is determined by a policy intervention. Let $F_{i2}(w)$ be the post-intervention cumulative distribution function of amenity quality w_{i2} at house i at time $t = 2$. Then:*

$$F_{i2}(w|w_{i1}) = F_2(w) \qquad \forall i, w$$

where $F_2(w)$ is a CDF that is shared by all houses in period 2 and is known by consumers when they purchase houses at the beginning of period 1. In periods 3 and onward, amenity quality at each house evolves independently according to the Markov process described in Assumption 1.

The key feature of Assumption 2 is that because of the policy intervention, period 1 amenity quality does not affect period 2 amenity quality. For example, for the coastal houses described in the previous section, Assumption 2 implies that all sections of beach are nourished to the same design width at the beginning of period 2, regardless their width in period 1. Then, in periods 3 onwards, each section of beach erodes and accretes independently according to a common Markov transition function. Thus, from the perspective of a consumer purchasing a house at the beginning of period 1, all houses have the same expected amenity quality in periods 2 onward.

Before proving the main result, I adopt one additional simplifying assumption: consumers' utility functions are quasilinear in the composite good c (or equivalently, quasilinear in income). Formally:

Assumption 3. ***Quasilinear Utility:*** *Consumer j's utility function is quasilinear in the composite good c:*

$$u(w, \pi, c; \theta_j) \equiv v(w, \pi; \theta_j) + k_j c \tag{6}$$

where $v(\cdot; \theta_j)$ may take any functional form and k_j is a constant representing consumer j's marginal utility of consumption for the composite good.

For notational convenience, let u_j represent the utility function for consumer j with preferences θ_j. I now state the main theoretical result:

Theorem 2. ***Discontinuity Matching Theorem:*** *Suppose that in equilibrium, consumer j purchases house i. Under the conditions described in Assumptions 2 and 3, consumer j's willingness to pay for a certain one-unit increase in amenity quality for period 1 only is given by the derivative of equilibrium housing prices with respect to period 1 amenity quality:*

$$\frac{\partial p}{\partial w_1}\bigg|_{w_{i1}} = \frac{\frac{\partial u_j}{\partial w}\Big|_{w_{i1}}}{\frac{r}{\rho} \cdot \frac{\partial u_j}{\partial c}} \tag{7}$$

Proof. Theorem 1 states that:

$$\frac{\partial p}{\partial w_1}\Big|_{w_{i1}} = \frac{\sum_{t=1}^{\infty}\left(\frac{1}{1+\rho}\right)^t E\left[\frac{\partial u_j}{\partial w}\big|_{w_t}\frac{\partial w_t}{\partial w_1}\big|_{w_{i1}}\right]}{\sum_{t=1}^{\infty}\left(\frac{1}{1+\rho}\right)^t E\left[r\frac{\partial u_j}{\partial c}\big|_{w_t}\right]} \tag{8}$$

By Assumption 3, marginal utility of consumption is constant, which implies that Equation (8) can be rewritten as:

$$\frac{\partial p}{\partial w_1}\Big|_{w_{i1}} = \frac{\sum_{t=1}^{\infty}\left(\frac{1}{1+\rho}\right)^t E\left[\frac{\partial u_j}{\partial w}\big|_{w_t}\frac{\partial w_t}{\partial w_1}\big|_{w_{i1}}\right]}{\frac{r}{\rho}\cdot\frac{\partial u_j}{\partial c}} \tag{9}$$

Decomposing the right-hand side into current and future terms shows that:

$$\frac{\partial p}{\partial w_1}\Big|_{w_{i1}} = \frac{\frac{\partial u_j}{\partial w}\big|_{w_{i1}}}{\frac{r}{\rho}\cdot\frac{\partial u_j}{\partial c}} + \sum_{t=2}^{\infty}\left(\frac{1}{1+\rho}\right)^t E\left[\frac{\frac{\partial u_j}{\partial w}\big|_{w_t}}{\frac{r}{\rho}\cdot\frac{\partial u_j}{\partial c}}\cdot\frac{\partial w_t}{\partial w_1}\Big|_{w_{i1}}\right] \tag{10}$$

This equation makes it clear that in equilibrum, the cost of purchasing an extra unit of the amenity depends on the (certain) marginal utility gained in period 1, plus the discounted expected marginal utility gained in future time periods.

Now note that Assumption 2 implies that $\frac{\partial w_t}{\partial w_1} = 0$ for all $t \geq 2$. In other words, changes in period 1 amenity quality have no effect on amenity quality in periods 2 onward. As a result, the future term in Equation (10) evaluates to zero and the equation simplifies to the result shown in Equation (7). □

Theorem 2 is the key theoretical contribution of this paper. It shows that marginal willingness to pay for a certain, immediate, one-unit, one-period increase in the amenity can be calculated directly from the cross-sectional relationship between housing prices and amenity quality in the year before a policy intervention occurs. This fact is of great empirical importance. Because housing prices and amenity quality are directly observable, the left-hand side of Equation (7) can be used to estimate a parameter that has an exact interpretation as marginal willingess to pay in a theoretically-consistent hedonic model. This estimate of marginal willingness to pay for a temporary increase in amenity quality can then be scaled up, using the discount rate, to estimate marginal willingness to pay for a permanent change in amenity quality.

The logic underlying Theorem 2 rests on the assumption that the policy intervention causes all houses to have the same expected amenity quality in period 2, regardless of their period 1 quality. To achieve this equalization, between periods 1 and 2 some houses experience a large discontinuity in amenity quality, and some experience a smaller discontinuity. Thus, although pre-intervention amenity quality differs across houses, all houses have identical predicted post-discontinuity quality. It is this "discontinuity matching" on the basis of expected period 2 amenity quality that justifies interpreting price differences between houses as a measure of willingness to pay for marginal improvements in period 1 amenity quality.

Like many theoretical results, the practical value of Theorem 2 depends on whether or not its predicates—particularly Assumption 2—are true in relevant real-world situations. I argue that as long as it is possible to control for idiosyncratic time shocks and fixed housing characteristics, then Assumption 2 will be true in a number of practically useful situations. For example, in the empirical section of this paper, I use discontinuity matching to estimate homeowners' willingess to pay for a home located on a wider section of beach, using the sharp and highly-predictable change in beach width caused by nourishment projects. By matching sections of beach that are predicted to have similar widths next period, this approach allows a comparison of the current period price of houses located on narrow sections of beach (that receive nourishment next period) against the price of houses located on wide sections of beach (that are not nourished next period). However, the methodology could also be applied in many other contexts. For example, it could be used to estimate marginal willingness to pay for construction of new subway or bus lines, based on the differential discontinuity in public transportation access caused by the opening of the new station or line.

4 Data

To support my analysis of the welfare costs of coastal shoreline loss, I have constructed a unique dataset on housing sales transactions, beach width, and nourishment projects, for properties located within 5 kilometers of the beach in sixteen coastal Florida counties. The dataset covers the period from 1983 to 2009, and includes 388 miles of Florida's coastline.

The sixteen counties included in the analysis are: Bay, Brevard, Broward, Charlotte, Duval, Escambia, Lee, Manatee, Martin, Miami-Dade, Palm Beach, Pinellas, Sarasota, Saint Johns, Saint Lucie, and Volusia. Figure 1 shows a map of these counties, and indicates coastal areas where beach width survey data are available. As the map shows, these counties are primarily located on Florida's Atlantic coast and southern Gulf coast. These counties were chosen because they collectively cover the majority of segments of shoreline designated as "critically-eroded" by the Florida Department of Environmental Protection (FDEP, 2011b).

Below, I describe each of the data sources in more detail.

4.1 Beach Width Data

I have compiled data on beach width from a database of coastal surveys maintained by the Florida Department of Enviromental Protection (FDEP, 2008a). Each record in the database represents the distance from a fixed coastal survey monument to the mean high water (MHW) mark along a particular segment of beach.[4] The survey monuments are spaced approximately 1,000 feet apart along much of the Florida coastline; thus, these data have a high level of geographic resolution. In most locations, surveys are available every few years between 1983 and 2009, with better coverage in recent years.

Because the survey monuments are not located at a consistent distance from the upper end of the beach, the MHW data do not represent absolute beach width. To calculate absolute beach width, I use georeferenced aerial photography data (FDEP, 2011a) to manually geocode the location of the upper end of the beach near each survey monument. For consistency in determining the upper end of the beach, I use the location of the most seaward manmade structure near each survey monument. I then calculate beach width as the distance from the upper end of the beach to the survey monument, plus the distance from the survey monument to the MHW mark, with a trigonometric adjustment to account for the angle at which the MHW survey measurements were taken.

[4] The mean high water mark represents the location on the beach reached by the average high tide.

4.2 Property Sales Data

I have collected data on approximately 1.1 million qualified housing sales transactions in the sixteen in-sample counties. These data are taken from electronic records maintained by the property appraisers' offices in each county. The data include sales information, such as sale date, sale price, and sale qualification, as well as property characteristics, including building type, acreage, and construction date.

I use two methods to geocode the location of each property. When possible, I link each property's parcel ID number to detailed GIS parcel maps obtained from the Florida Department of Revenue (FDEP, 2011). In cases where there is no match, I geocode the property's street address using ESRI's ArcMap Business Analyst, using address point data when available and otherwise using an offset of 70 feet from the address location along the street centerline. I then link each geocoded address to the nearest GIS parcel, and use that parcel for subsequent analysis.

For each parcel, I then calculate the distance to the coast. I also assign each parcel-by-year observation a beach width measurement, based on beach width at the nearest FDEP survey monument.

4.3 Nourishment Data

I have constructed a list of beach nourishment projects using data from several sources. My primary source is a database compiled by researchers at Western Carolina University (WCU, 2008). This database lists 361 beach nourishment projects that took place in Florida between 1944 and 2006. I supplement this data with information from Florida State University's beach erosion control database, a list of ongoing nourishment projects maintained by the Florida Department of Environmental Protection, and a variety of other sources (e.g., FSU, 2008b; FDEP, 2009). After merging these data and eliminating duplicate and out-of-sample records, I generate a dataset that represents the near-universe of nourishment projects that took place between 1983 and 2009 in the 16 in-sample counties.

Table 1 provides detailed information about a subset of the largest nourishment projects included in the analysis. The table shows the set of variables that I have been able to collect for each nourishment project, including the year the project was completed, the project location, the cost of the project, the volume of sand deposited, and the length of beach nourished. Unfortunately, not all variables—particularly costs—are available for all nourishment projects.

Table 2 describes the characteristics of the 204 projects included in my analysis. The table shows that the average project placed 700,000 cubic yards of sand (roughly 900,000 tons) onto a 3.8 mile segment of beach, for an average nourishment intensity of approximately 47 cy/ft. The average cost of a nourishment project was $6.6 million. The table also summarizes the characteristics of a set of "major" projects with nourishment intensities of at least 25 cy/ft. As expected, these projects had higher volumes, covered more shoreline, and had higher costs.

4.4 Summary Statistics

Table 3 summarizes basic characteristics of the properties and beaches included in the main analysis, for the subset of properties located within 20 meters of a beach. The results are disaggregated into three categories based on the number of nourishments that took place at each FDEP marker between 1980 and 2010. The top two panels show that housing and beach characterisics in nourished areas differ significantly from housing and beach characteristics in areas that are never nourished.

The third panel in Table 3 describes the number of sales that occur in each five year period between 1980 and 2010, for properties located within 20 meters of the beach. The panel shows that there are 41,187 sales at FDEP survey monuments that are never nourished, 65,757 sales at monuments with one or two nourishments, and 11,803 sales at monuments with three or more nourishments. The number of sales increases over most of the sample, reaching a peak in 2000-2004 (at the height of the housing bubble) and then falling off in more recent years.

The fourth panel in Table 3 shows the number of geographic units represented by properties within 20 meters of the beach. There are 45,145 such properties, located near 1,304 FDEP survey monuments in 67 six-mile-long "zones". I have defined these zones as contiguous sections of coastline that span six miles each. Because the beach width data shows substantial spatial correlation between adjacent FDEP monuments (which are only 1,000 feet apart on average), I cluster and weight all regression results in this paper at the level of these zones.

An important constraint on my analysis is the availability of survey data on beach width. Figure 2 shows the availability of beach width data, by year and location along the coastline. As the figure indicates, data on beach width is available in only about a third of the survey monument-by-year combinations. This missing data is a serious concern for my panel and discontinuity matching regressions. I deal with this problem in two ways. In the repeat sales panel regressions, I adopt the assumption that the data are missing at random after controlling for property and time fixed effects. In the discontinuity matching approach, I use imputed width data.[5] However, note that because the differences-in-differences regressions do not require data on beach width, they are not affected by the missing data issue. The availability of this unbiased approach alleviates concerns about data problems in the other two approaches.

Figure 2 also shows the location and timing of beach nourishment projects. Several patterns are evident from the figure. First, many segments of beach are nourished at somewhat regular intervals, ranging from three to ten years. Second, nourishments only occur at certain segments of coastline.

Finally, Figure 3 shows a histogram of the distribution of beach width across all monument-by-year observations. The figure shows that the modal beach width is approximately 140 feet, and that the distribution of beach width has a long right tail. As the figure indicates, most beaches are between 25 and 400 feet wide.

5 Econometric Approach

In this paper I take three distinct econometric approaches to estimating homeowners' willingness to pay for wider beaches: (1) a repeat sales panel approach; (2) a differences-in-differences approach; and (3) a new "discontinuity matching" approach. In the following subsections, I explain how each research design uses housing market data to estimate $\frac{\partial p_t}{\partial w_t}\big|_{w_{it}}$, the partial derivative of the housing price function at time t with respect to beach width at time t. Under the assumption that the structural model described in Section 3 captures the main features of housing markets in

[5] I impute missing beach width data using an expectation-maximization algorithm that employs a Kalman filter followed by smoothing. Details about the imputation procedure are available upon request.

coastal Florida, I use Theorems 1 and 2 to provide direct welfare interpretations for the estimated coefficients.

5.1 Repeat Sales Panel Approach

I begin by using a repeat sales panel approach to develop an estimator for $\frac{\partial p_t}{\partial w_t}\Big|_{w_{it}}$. By Theorem 1 from Section 3, this partial derivative is equal to the marginal consumer's willingness to pay for a one-time policy intervention that adds one foot of sand to the beach in front of house i at time t (i.e., a one-foot beach nourishment project in which the sand is allowed to erode freely in subsequent periods). To motivate the estimator for this derivative, I adopt the following notation.

Let each beachfront house i belong to a neighborhood n, where n represents closest FDEP survey monument (so that the average neighborhood includes roughly 1000 feet of shoreline). Let p_{nit} represent the sale price of house i in neighborhood n in year t, and let w_{nt} describe beach width in neighborhood n in year t. As before, π_i represents unobservable permanent characteristics of house i. Additionally, let τ_t capture aggregate housing market shocks in year t, and let ϵ_{nit} be a normally distributed, zero-mean error term, with variance σ^2, that captures other sources of variation in price.

Following common practice in the hedonics literature, I assume that the price function $p_{nit} \equiv p(w_{nt}, \tau_t, \pi_i, \epsilon_{nit})$ takes a log-linear functional form. However, to allow for more flexibility in the relationship between price and beach width, I use a semi-parametric specification for w_{nt}. Let the binary variables $w_{nt}^0, w_{nt}^{50}, ..., w_{nt}^j, ..., w_{nt}^{500}$ indicate whether beach width in neighborhood n in year t is between j feet and $j + 50$ feet. I then assume that the price function can be written as:

$$\log p_{nit} = \sum_j \beta_j w_{nt}^j + \tau_t + \pi_i + \epsilon_{nit} \tag{11}$$

Equation (11) suggests calculating marginal willingness to pay for a policy intervention using the following approximations to the partial derivative of price with respect to width:

$$E\left[\frac{\partial p}{\partial w_t}\Big|_{w_t=w^j}\right] \approx E\left[\frac{p(w^J,\tau_t,\pi_i,\epsilon_{nit}) - p(w^0,\tau_t,\pi_i,\epsilon_{nit})}{w^J - w^0}\right]$$
$$= \frac{(e^{\beta_J} - e^{\beta_0})e^{\tau_t+\pi_i+(\sigma^2/2)}}{w^J - w^0} \tag{12}$$

where with some mild abuse of notation, I let $w^j \equiv j$ indicate the lower end of the jth beach width bin.

To estimate willingness to pay using Equation (12), I first use panel data on repeat housing sales to estimate Equation (11) using ordinary least squares. The identifying assumption is that conditional on the year and house fixed effects, variation in beach width is orthogonal to any other housing price determinants captured in the error term. Because beach width at adjacent survey monuments is highly correlated, I cluster standard errors by six-mile-long sections of beach. Additionally, to improve the efficiency of the estimates, I weight each observation by the sum of the inverse of the total number of housing sales in its neighborhood. Then, in a second step, I substitute the estimated coefficients from Equation (11) into Equation (12) and calculate the marginal willingness to pay estimate $\widehat{\frac{\partial p}{\partial w_t}}\big|_{w_t}$.

5.2 Differences-in-Differences Approach

One potential concern about the repeat-sales approach is that within particular neighborhoods, long-term changes in beach width may be correlated with changes in long-term determinants of housing prices. For example, as neighborhoods become wealthier, they may make more frequent investments in beach nourishment. In the panel model from the previous section, this would create correlation between the beach width bin variables and the error term.

To address this possibility, I implement a differences-in-differences regression approach based on abrupt changes in beach width caused by nourishment projects. Again, the goal is to estimate the derivative $\frac{\partial p_t}{\partial w_t}\big|_{w_{it}}$. The advantage of a differences-in-differences approach is that the factors that influence the decision to nourish a particular stretch of beach—such as neighborhood wealth and political influence—are likely to evolve slowly over time. Thus, after inclusion of appropriate fixed effects, the sudden increase in beach width caused by beach nourishment is likely to be orthogonal to other determinants of housing prices.

Unfortunately, the disadvantage of a differences-in-differences approach is that it fits less well into the structural model that provides a welfare interpretation for the derivative $\frac{\partial p_t}{\partial w_t}\Big|_{w_{it}}$. Theorem 1 depends on the assumption that changes in beach width can be modeled as a Markov process. To argue that beach nourishment fits this assumption requires that (1) homebuyers have no advance knowledge of beach nourishment projects, and (2) the decision to nourish beaches is random, conditional on beach width in the previous period. Neither assumption is a perfect description of reality. However, for the purposes of this section, I proceed as if both assumptions hold. Then, in the following section, I describe a discontinuity matching design that is better able to estimate the welfare effects of deliberate policy interventions.

I implement the differences-in-differences approach in two steps. First, I divide the coastline into one-mile "neighborhoods" and then use houses with repeat sales to develop a housing price index for each of these neighborhoods. Second, I run differences-in-differences regressions on a dataset that includes five years of forward and backward lagged data for each neighborhood-by-year observation.

The following subsections describe these two steps in more detail.

5.2.1 Step 1: Neighborhood Housing Price Indices

Before running the differences-in-differences regressions, I estimate a separate housing price index for each one-mile beachfront neighborhood. Developing price indices serves two purposes. First, it removes variation in prices that can be attributed to fixed idiosyncratic characteristics of individual houses. Second, it transforms an unbalanced panel of housing sales transactions, which contains only two or three sales per house, into a balanced panel of price indices with an observation for almost every year and neighborhood combination. Because there is only modest variation in beach width across individual FDEP survey monuments within one-mile sections of coastline, this transformation sacrifices little information about the relationship between housing prices and beach width. Using a price index rather than raw housing sales data is necessary because I include only five years of forward and backward lagged data for each neighborhood-by-year observation.

To estimate the price indices, I model the price function $p_{nit} \equiv p(P_{nt}, \pi_i, \epsilon_{nit})$ as depending on three sets of parameters: fixed effects P_{nt} that capture all sources of neighborhood-by-year variation in housing prices, house fixed effects π_i that reflect fixed characteristics of house i, and a zero-mean error term ϵ_{nit}. The fixed effects P_{nt} represent the price index for neighborhood n in year t. I assume that these parameters enter the price function according to the following log-linear functional form:

$$\log p_{nit} = \pi_i + \tau_{nt} + \epsilon_{nit} \tag{13}$$

where I define $\tau_{nt} \equiv \log(P_{nt})$. I estimate this equation using OLS, and then use the estimated coefficients to calculate the price index $P_{nt} = \exp(\tau_{nt})$ for each neighborhood and year unit.

It is important to note that any subsequent regression of this price index on other housing and neighborhood variables will be consistent only if: (i) the regression includes neighborhood fixed effects, and (ii) none of the independent variables vary at the level of individual houses.

5.2.2 Step 2: Differences-in-Differences Regressions

The differences-in-differences research design uses changes in housing prices at beaches that are not nourished to generate a counterfactual for changes in housing prices at beaches that are nourished. This comparison depends on the identifying assumption that in the absence of nourishment, the trend in prices at nourished beaches would have been similar to the trend in prices at unnourished beaches.

To run differences-in-differences regressions, I construct a dataset that includes five years of pre-data and four years of post-data for each neighborhood-by-year observation. Let t represent the base year for each set of observations, and let l represent time elapsed since the base year. Thus, each neighborhood-by-year observation appears ten times, as $(n, t, l) = (n, t+5, -5), ..., (n, t-1, -1), (n, t, 0), ..., (n, t-4, 4)$. I then assume that the housing price index function $P(N_{nt}, \tau_{tl}, \pi_{nt})$ can be modeled as:

$$P_{ntl} = \sum_{s=-5}^{4} \beta_s N_{nt} \cdot \mathbf{1}\{l = s\} + \tau_{tl} + \pi_{nt} + \epsilon_{ntl} \tag{14}$$

In this equation, N_{nt} is a dummy variable that indicates that the beach near neighborhood n was nourished in the base year t. The indicator $\mathbf{1}\{l = s\}$ takes value 1 if $l = s$, and zero otherwise. The year-by-elapsed year fixed effects τ_{tl} capture aggregate housing market shocks, and the neighborhood-by-base year fixed effects π_{ntl} capture fixed neighborhood characteristics of neighborhood n for the set of ten elapsed observations with common base year t. Because of the possibility that adjacent neighborhoods do not represent independent observations, I cluster standard errors by six-mile-long sections of beach.

I also develop a similar differences-in-differences model of beach width. Using the same dataset of pre- and post-data, I model the beach width $w_{ntl} \equiv w(N_{nt}, \lambda_{tl}, \kappa_{nt})$ as follows:

$$w_{ntl} = \sum_{s=-5}^{4} \phi_s N_{nt} \cdot \mathbf{1}\{l = s\} + \lambda_{tl} + \kappa_{nt} + \zeta_{ntl} \tag{15}$$

In this equation, w_{ntl} represents beach width in neighborhood n in year t, lagged l years. The binary variable N_{nt} indicates that the beach in neighborhood n was nourished in year t, and the indicator $\mathbf{1}\{l = s\}$ takes value 1 if $l = s$, and zero otherwise. The base year-by-elapsed year fixed effects λ_{tl} capture aggregate shocks to beach width, and the neighborhood-by-base year fixed effects κ_{nt} capture fixed differences in beach width between neighborhoods, for sets of elapsed observations with the same base year. The zero-mean error term ζ_{ntl} captures other sources of variation in beach width.

The rationale for constructing this "stacked" dataset is that because beach width approximately follows a random walk, the fixed-effects approach embedded in a differences-in-differences design is not really an appropriate model. However, by limiting each fixed effect to include only ten years of data, I minimize inaccuracies by modeling changes over only a short period of time. Note that because I estimate separate coefficients for each forward and backward lag of beach nourishment, and because I cluster standard errors by neighborhood and base year, duplicating observations in this way does not raise concerns about overestimating the precision of the coefficients.

To use the differences-in-differences results to calculate the derivative $\frac{\partial p_t}{\partial w_t}\Big|_{w_{it}}$, I first estimate Equations (14) and (15) using OLS. I then approximate the average derivative of price with respect to beach width as:

$$E\left[\frac{\partial p}{\partial w_t}\Big|_{w_t}\right] \approx E\left[\frac{P(N_{nt}=1,\tau_{t0},\pi_{nt}) - P(N_{nt}=0,\tau_{t0},\pi_{nt})}{w(N_{nt}=1,\lambda_{t0},\kappa_{nt}) - w(N_{nt}=0,\lambda_{t0},\kappa_{nt})}\right]$$
$$= \frac{\beta_0}{\phi_0} \tag{16}$$

Under the assumptions discussed above and in Theorem 1, this derivative represents willingness to pay for a one-time beach nourishment project that adds one foot of sand to the beach in the current year.

In addition to the main differences-in-differences specification discussed above, I also run alternative regressions in which I break down the impacts of beach nourishment based on the intensity of each project (measured in cubic yards of sand added per foot of coastline). I divide nourishments into four categories: 1 to 24 cy/ft, 25 to 50 cy/ft, 50 to 74 cy/ft, and 75 or more cy/ft. I then run differences-in-differences regressions for price and width that include separate sets of nourishment variables for nourishments in each of these categories. Using these coefficients, I then generate several alternative estimates of the derivative $\frac{\partial p_t}{\partial w_t}\big|_{w_{it}}$.

5.3 Discontinuity Matching Approach

The repeat sales and differences-in-differences designs from the previous sections both have drawbacks. Although Theorem 1 provides a strong theoretical foundation for the repeat sales design, this approach is vulnerable to omitted variables that change over time within neighborhoods. In contrast, although the differences-in-differences design is a more robust empirical approach, using Theorem 1 to give a welfare interpretation to coefficients from differences-in-differences regressions requires somewhat unrealistic assumptions.

To overcome the limitations of these two approaches, in this section I describe a new "discontinuity matching" research design, motivated by Theorem 2, that uses predictable discontinuities in beach width to identify marginal willingness to pay. The goal of this procedure is to develop an estimate of the derivative $\frac{\partial p_t}{\partial w_t}\big|_{w_{it}}$ from Theorem 2. Recall that under the conditions specified in Theorem 2, this derivative expresses the marginal consumer's willingness to pay for an immediate, one-period, marginal increase in beach width. For this result to hold, prospective homebuyers must be aware that next period, the government will implement a beach nourishment project that will cause a discontinuity in beach width along some sections of coastline. I argue that this condition is a reasonable approximation of reality.

Implementing the discontinuity matching research design requires three steps. First, I divide beachfront houses into mile-long neighborhoods, and then estimate a housing price index for each neighborhood-by-year cell. This step removes cross-sectional variation in price that can be attributed to fixed characteristics of individual houses. Second, I develop a simple rational model of homebuyers' beliefs about the effect of nourishment projects on beach width, and then estimate the parameters of this model using historical data on beach width. Third, I use a nearest-neighbor matching procedure to identify sets of neighborhood-by-year units that are predicted to have similar beach width in the following year (based on the empirical belief model). Within each matched set, all neighborhoods share the same next-period predicted beach width. However, some neighborhoods reach that next-period beach width by being nourished; some reach it without nourishment. Thus, I use the matching procedure to estimate the treatment effect of *next-period* nourishment on the *current* width and price index of these two sets of neighborhoods, and then use these treatment effects to calculate the pre-intervention cross-sectional derivative between price and beach width. Under Theorem 2, this derivative can be interpreted as the marginal rental value of widening the beach by one foot for one year.

I now discuss these three steps in more detail.

5.3.1 Step 1: Estimate Neighborhood Housing Price Indices

I begin the discontinuity matching procedure by estimating a separate housing price index for each one-mile-long beachfront neighborhood. As in the differences-in-differences approach, developing price indices removes variation in prices that can be attributed to fixed characteristics of individual houses, and transforms an unbalanced panel of housing sales into a balanced panel of neighborhood price indices. Because there is relatively little variation in beach width within these one-mile neighborhoods, this transformation sacrifices little information about the relationship between housing prices and beach width.

To estimate the neighborhood price indices, I follow the procedure described previously in Section 5.2.1.

5.3.2 Step 2: Model Homebuyers' Beliefs about Beach Width

The second step of the discontinuity matching procedure is to develop and estimate a model of homebuyers' beliefs about the evolution of beach width over time. Although there are a variety of possible belief structures, I assume a simple model in which a consumer who buys a house knows current beach width, as well as whether the beach will be nourished the following year, and makes rational predictions based on this information.[6] More formally, let a consumer's information set at time t include current width w_{nt} and a next-period nourishment indicator $N_{n,t+1}$, for every neighborhood n. The consumer believes that the evolution of beach width over time follows an AR(1) process:

$$w_{nt} = \kappa + \alpha w_{n,t-1} + \phi N_{nt} + \zeta_{nt} \tag{17}$$

in which current beach width w_{nt} depends on a constant term κ, previous-year beach width $w_{n,t-1}$, a current nourishment indicator N_{nt}, and a normally-distributed zero-mean error term ζ_{nt}. I assume the consumer's information set includes the parameters κ, α, and ϕ that govern this system.

Equation (17) is a simplistic model of the true transition function for beach width. Sand erosion and accretion are complex processes that are governed by complicated longshore sediment transport equations that include variables such as sand grain size, shore profile, and prevailing currents (Van Wellen, Chadwick, and Mason, 2000). However, because consumers are unlikely to have a sophisticated understanding of the factors that influence beach width, Equation (17) may nonetheless represent an appropriate model of consumers' beliefs. Furthermore, this reduced form model is consistent with the necessary conditions stated in Theorem 2—in particular, that beach width may be affected by a policy intervention but otherwise follows a Markov process.

To generate an estimate of consumers' beliefs about next-period beach width for every neighborhood-by-year observation, I estimate Equation (17) using OLS, using panel data on beach width and the timing and location of nourishment projects. I then use the estimated coefficients to predict beach

[6]Poor et al (2001) show that objective measures of environmental quality perform as well as subjective measures in explaining home prices.

width in the following period ($\hat{w}_{n,t+1}$), as follows:

$$\hat{w}_{n,t+1} \equiv \kappa + \alpha w_{nt} + \phi N_{n,t+1} \tag{18}$$

5.3.3 Step 3: Estimate Willingness To Pay Using Nearest Neighbor Matching

The goal of the discontinuity matching procedure is to develop an estimate of the cross-sectional partial derivative of current housing prices with respect to current beach width, for matched neighborhoods with beaches that are predicted to have the same beach width in the following period. Under Theorem 2, this derivative has an interpretation as marginal willingness to pay for an extra year of improved beach width. To explain the nearest neighbor matching procedure that I use to estimate this derivative, I adopt the Rubin potential outcomes framework (Rubin, 1974; Rosenbaum and Rubin, 1983).

Suppose that at the beginning of year t, consumers believe that the beach near neighborhood n will be $\hat{w}_{n,t+1}$ feet wide in year $t+1$. Based on the model of beliefs presented in Equation (17), there are only two ways that this could happen: either the beach is nourished at the beginning of year $t+1$, or it is not. Let $N_{n,t+1}$ be a binary treatment variable that takes value 1 if beach nourishment occurs at neighborhood n in year $t+1$, and 0 otherwise. Now, let $w_{nt}(1)$ and $w_{nt}(0)$ denote the two potential outcomes for beach width at beach n in year t, depending on the value of the treatment $N_{n,t+1}$. For example, $w_{nt}(1)$ denotes beach width in neighborhood n and year t when the beach in this neighborhood is nourished in year $t+1$ (i.e., $N_{n,t+1} = 1$). Similarly, let $P_{nt}(1)$ and $P_{nt}(0)$ be the two potential outcomes for the housing price index in neighborhood n in year t, where again the treatment $N_{n,t+1} \in \{0, 1\}$ indicates whether nourishment occurs in neighborhood n in year $t+1$.

Casting the problem in this potential outcomes terminology is counterintuitive, given that the actual observed outcomes w_{nt} and P_{nt} are determined *before* the beach nourishment project takes place in year $t+1$. Furthermore, given that next-period nourishment is more likely at beaches that are currently eroded, it would appear that the treatment $N_{n,t+1}$ is a function of the observed outcome w_{nt}, not vice versa. The resolution of this apparent contradiction relies on the memorylessness property of Markov models. To understand the intuition, adopt for the moment the perspective of an observer under a "veil of ignorance", to whom only $\hat{w}_{n,t+1}$ is observable. For this observer, learning the two potential outcomes that beach width could have taken in period t would add no additional information about whether the beach is nourished in year $t+1$. In other words, conditional only on predicted next period width, whether the beach was nourished in year t is as good as randomly assigned—which means that the outcomes can be viewed in a quasi-experimental framework.

More formally, consider the two key conditions required for a matching estimator to generate the same consistent inference as a randomized experiment: (i) the probability that any particular unit is assigned to the treatment group must be greater than zero and less than one; and (ii) conditional on observable covariates, the treatment must be independent of the potential outcomes (Abadie and Imbens, 2011). Condition (i) is clearly satisfied by limiting the sample of neighborhoods to those with at least one beach nourishment in one year. The argument that condition (ii) is satisfied requires an assumption about the characteristics of neighborhoods that receive beach nourishment. In particular, it requires that there are no omitted variables that are correlated with both beach width and housing prices. For the remainder of the analysis, I assume that this assumption—that conditional on the covariate $\hat{w}_{n,t+1}$, the treatment $N_{n,t+1}$ is independent of the potential outcomes $w_{nt}(1)$ and $w_{nt}(0)$—is true.

Given the potential outcomes defined above, I now follow Abadie and Imbens (2011) and develop nearest neighbor matching estimators for the treatment effects of next-period nourishment on current beach width and current housing price indices. Consider first the population average treatment effect for the subpopulation of treated units (PATT) for current beach width:

$$PATT_w = E[w_{nt}(1) - w_{nt}(0)|N_{n,t+1} = 1] \tag{19}$$

Because both $w_t(1)$ and $w_t(0)$ cannot both be observed for the same unit, I use a nearest neighbor matching strategy to estimate the unobserved outcomes. This procedure selects, for each treated unit, the set of k untreated units that are most similar on the basis of a vector of matching variables $\mathbf{X}_{nt}$ that includes $\hat{w}_{n,t+1}$. The comparison of similarity between a treated unit and an untreated unit is based on a distance metric calculated as the norm of the vector of differences between the vectors of matching variables for the treated and untreated unit. Let Ω_{nt} denote the set of k untreated units that are nearest neighbors for treated observation nt. I estimate the unobserved potential outcomes $w_{nt}(0)$ as:

$$\hat{\hat{w}}_{nt}(0) = \sum_{m \in \Omega_{nt}} \frac{1}{k} w_{mt} \tag{20}$$

for units nt for which $N_{n,t+1} = 1$. I then use this estimated potential width outcome to create a matching estimator for the PATT:

$$\widehat{PATT}_w = \frac{1}{q} \cdot \sum_{nt:N_{n,t+1}=1} (w_{nt}(1) - \hat{\hat{w}}_{nt}(0)) \tag{21}$$

where q represents the number of treated observations, i.e., observations nt for which $N_{n,t+1} = 1$.

I use a similar procedure to estimate the PATT for the price index. I define the PATT as:

$$PATT_P = E[P_{nt}(1) - P_{nt}(0) | N_{n,t+1} = 1] \tag{22}$$

I then estimate the unobserved potential price outcomes for treated units as:

$$\hat{\hat{P}}_{nt}(0) = \sum_{m \in \Omega_{nt}} \frac{1}{k} P_{mt} \tag{23}$$

and the PATT as:

$$\widehat{PATT}_P = \frac{1}{q} \cdot \sum_{nt:N_{n,t+1}=1} (P_{nt}(1) - \hat{\hat{P}}_{nt}(0)) \tag{24}$$

Now return to the problem of estimating the pre-nourishment cross-sectional relationship between housing prices and beach width. A natural way to estimate the derivative of price with respect to width, evaluated at the potential width outcome $w_t(0)$ in year t, is:

$$\begin{aligned} \widehat{\frac{\partial p}{\partial w_t}}\Big|_{w_t(0)} &= E\left[\frac{P_t(1) - P_t(0)}{w_t(1) - w_t(0)}\right] \\ &= \frac{\widehat{PATT}_P}{\widehat{PATT}_w} \end{aligned} \tag{25}$$

6 Results

In this section I present the main empirical results from my analysis. I begin with the results from the repeat sales research design.

6.1 Repeat Sales Results

To establish a baseline against which to compare later results, Columns (1) and (2) of Table 4 present the results from "conventional" OLS hedonic regressions of log sales price on housing characteristics and semi-parametric beach width dummy variables. Column (1) presents results for all properties; Column (2) presents results for only properties with repeat sales. These regressions control for year-by-county and year-by-housing type (condo vs single family) fixed effects, but do not include property fixed effects. The coefficients show that prices increase with beach width, at least for beaches less than 300 feet wide. For example, Column (2) shows that a house located on a beach that is 0 to 49 feet wide has a sale price that is 5.4 percent lower than a house located on a beach that is 200 to 249 feet wide.

Columns (3) and (4) of Table 4 show results from similar regressions based on a repeat-sales approach. Unlike the conventional OLS regressions, the repeat sales regressions include property fixed effects that control for idiosyncratic characteristics of each individual house or condo. These regressions show a much more modest relationship between sales price and beach width. A house in the 0-49 foot category sells for a statistically insignificant 1.9 percent less than a house in the 200-249 foot category.

Figure 4 compares the conventional and repeat-sales coefficients from Columns (2) and (3) of Table 4. The figure emphasizes the fact that the conventional results overstate the relationship between price and width, relative to the repeat sales approach. Although both approaches suggest that houses with less than 100 feet of beach experience a modest price discount, the magnitude of this discount is much greater in the conventional coefficients.

Figure 5 presents an alternative repeat-sales specification, based on a more detailed set of 10-foot beach width bins. The figure confirms the general patterns from the main repeat-sales analysis.

However, the point estimates from this figure show that homes located with less than 20 feet of beach sell for a price discount of between 6 and 14 percent, compared to houses with 200 feet of beach. This discount is highly suggestive, but only marginally statistically significant.

6.2 Differences-in-Differences Results

6.2.1 Assessment of Research Design

Before presenting the main differences-in-differences results, I present evidence on the appropriateness of the research design. One important question is whether the timing of beach nourishment projects is related to the characteristics of parcels that are sold. For the differences-in-differences design to be valid, nourishment must not be correlated with unobservable parcel characteristics. Although this criterion is fundamentally untestable, it is more likely to be true if nourishment is uncorrelated with observable property characteristics.

Table 5 summarizes the characteristics of parcels that are sold in the two years before and after nourishment. The table shows that housing characteristics are strongly balanced before and after nourishment. Across a variety of characteristics—including vacancy, parcel acreage, living area, year built, and number of bedrooms and bathrooms—there are no statistically significant differences in pre- and post- characteristics. The primary characteristics that do show a significant relationship with nourishment timing are beach width, nourishment status, and nourishment intensity.

Another important test of a differences-in-differences design is whether the control group has a similar pre-intervention trend to the treatment group. Figure 6 plots the aggregate trend in the neighborhood housing price indices for six groups, based on the most recent five-year period in which the beach was nourished. The figure shows that homes in these different categories do experience very similar price trends. However, the data are somewhat noisy, suggesting that it may be important to control for other sources of variation, such as county-by-year price trends.

A final criterion for the research design is whether the intervention has a meaningful effect, i.e., whether nourishment increases beach width. Table 6 presents the results from estimating Equation (15), which compares the width of beaches that are nourished and unnourished in a particular year.

The table shows that nourishment causes a sharp, highly significant increase in width. Compared to the previous year, the average section of beach gains 83 feet in width in the year of nourishment (with a 95 percent confidence interval of 59 to 97 feet). Overall, the coefficients show an intuitive pattern: the beach erodes in the years before nourishment, gains considerable width in the year of nourishment, and then continues eroding.

As a further test of the nourishment intervention, Table 7 shows the results from estimating the change in beach width as a function of nourishment intensity (cubic yards of sand placed per foot of beach). The table shows results for three intensity categories, 25 to 49 cy/ft, 50 to 74 cy/ft and >75 cy/ft, relative to the omitted category of no nourishment (results for the 1-24 cy/ft category are similar but not shown). The coefficients show that changes in width are strongly increasing in nourishment intensity. For example, nourishments in the 25-49 cy/ft category cause the beach to increase by an additional 57 feet, whereas nourishments in the >75 cy/ft category cause the beach to increase by an additional 121 feet.

6.2.2 Main Differences-in-Differences Results

Table 8 shows the results of estimating Equation (14), which compares the housing price index for one-mile neighborhoods located near beaches that are nourished or unnourished in a particular year. To allow for the possibility that beach width may be more important for houses located closer to the beach, the table presents separate results for properties in three different distance categories: 0 to 19 meters from the beach, 20 to 799 meters from the beach, and 800 to 5,000 meters from the beach.

The regression results in all three categories reveal a consistent pattern: nourishment projects have no effect on sales prices. For example, for parcels located directly on the beach (the 0-19 meters category), the coefficients imply that housing prices increase by a statistically insignificant 1.2 percent between two years before nourishment and the year of nourishment, with a 95 percent confidence interval of -2.5 percent to +4.9 percent. To illustrate the results, Figure 7 plots changes in beach width and changes in housing prices (in the 0-19 meters category), relative to the number of years elapsed since nourishment. The figure emphasizes the fact that although nourishment causes a sharp change in beach width, it has no immediate effect on housing prices.

Table 9 presents the results of an alternative differences-in-differences specification that compares the change in prices accompanying high-intensity nourishments against the change in prices accompanying low-intensity nourishments. The results again reveal that housing prices do not respond to the timing of nourishment projects. As shown in Figure 8, even though higher intensity nourishments cause greater increases in beach width, these changes in beach width are not reflected in housing prices, which show no obvious relationship to the timing of nourishment.

6.3 Discontinuity Matching Results

The discontinuity matching procedure includes two substantive components: developing a rational model of beliefs about future beach width, and using a nearest neighbor matching procedure to calculate the treatment effect of future beach nourishment on current beach width and housing prices.

Table 10 shows the results of estimating a model of beliefs about beach width corresponding to Equation (17). Column (1) represents the simplest possible AR(1) specification, in which beach width is modeled as a function of lagged beach width, a binary nourishment variable, and a constant. The results indicate that beach width is highly autocorrelated, with a coefficient of .91 on lagged width, and that nourishment causes a 66 foot increase in beach width. The coefficients are very precisely estimated.

Columns (2A) through (2E) show the results of estimating separate results for beaches with 1, 2, 3, 4, or 5 nourishments, respectively, during the period from 1983 to 2009. The rationale for estimating separate regressions is that beaches that erode at faster rates may also be nourished more frequently. The regressions results confirm this hypothesis: the coefficient on lagged width decreases from .93 and .91 at beaches with 1 or 2 nourishments to .82 and .88 at beaches with 4 or 5 nourishments. Furthermore, the effects of nourishment on beach width are larger at beaches that are nourished less frequently.

Figure (9) illustrates the results from the matching stage of the discontinuity matching procedure. The top panel shows how beach width evolves over time for two groups of neighborhood-by-year observations: neighborhoods that are nourished (“treated units”), and similar unnourished neighborhoods that are predicted to have similar beach width in the following year ("control units"). The panel shows that the treated and control neighborhoods have reasonably similar beach width in the year of nourishment, as would be expected, given that these units are matched on predicted width for that year. In subsequent years, the treated and control groups also show similar trends, which is encouraging and suggests that the Markov assumption underlying the discontinuity matching approach is valid. However, in the year before nourishment, the treated neighborhoods show a substantial decline in beach width relative to the control group. From the perspective of the discontinuity matching procedure, this decline is the treatment effect of nourishment on pre-nourishment beach width.

The second panel of Figure (9) shows similar results for the effect of nourishment on pre-nourishment housing prices. Again, the panel shows that the treatment and control groups have similar values of the price index in the year of nourishment, and experience similar post-nourishment price trends. Unlike the width results, however, the panel shows that there is no discernable effect of nourishment on pre-nourishment housing prices. In other words, the treatment effect of predictable future beach nourishments on current housing prices is statistically indistinguishable from zero.

Table 11 presents estimates of the population average treatment effect on the treated (PATT) from Equations (21) and (24). These estimates confirm the qualitative results from Figure (9) . Although next-period nourishment is associated with a highly significant 60 foot decrease in current beach width, it is linked to an insignificant decrease of $1,729 in the current housing price index. Combining these two treatment effects suggests that the average homeowner is willing to pay $29 to rent an extra foot of beach for one year. Because this estimate represents the ratio of two random variables with possibly correlated distributions, I do not calculate a standard error or a confidence interval. However, the significant uncertainties in the treatment effect for price suggest it would be difficult to reject the null hypothesis that willingness to pay is $0.

7 Discussion and Policy Implications

7.1 Summary of Main Results

The empirical results from the previous section are striking. Using three different research designs, I find consistent evidence that homeowners place little value on the width of coastal beaches. The repeat-sales regressions suggest a statistically signficant positive effect of beach width on prices, but the effect is small, and only holds for houses located on beaches that are less than 250 feet wide. Furthermore, because these panel regressions do not control for factors that change over time within neighborhoods (e.g., wealth, political influence), there is a possibility that the direction of causality runs from prices to beach width, not vice versa. In contrast, based on the differences-in-differences regressions and the discontinuity matching results, I am unable to reject the null hypothesis that homeowners' willingness to pay to avoid coastal shoreline loss is zero.[7] Since these two research designs are based on sharp variation in beach width caused by nourishment projects, they are more likely to identify the true causal effect of width on price.

However, the results also suggest a second important finding: the marginal benefits of an extra foot of beach may be highly nonlinear. The repeat-sales results show that the relationship between housing prices and beach width is only positive for houses with less than 250 feet of beach. Furthermore, houses with extremely eroded beaches sell for a substantial discount. In particular, the point estimates indicate that houses with less than 20 feet of remaining beach have sales prices that are 6 to 14 percent lower than houses with 200 feet of beach. Because the repeat sales design has weaknesses, and because I observe relatively few homes located on beaches with such high levels of erosion, this conclusion should not be overemphasized. Nonetheless, it suggests the possibility that the welfare costs of sea level rise may be low up to a threshold, and then increase sharply.

[7]This finding is particularly striking in light of the large amount of money that has been spent on beach nourishment over the last 50 years (U.S. ACE, 1996). However, historically, beach nourishment has been heavily subsidized by the U.S. and Florida governments, with local communities paying less than half of the actual cost of beach nourishment (NRC, 1995; U.S. ACE, 1996). Thus, the decision to nourish a particular beach may not be a valid measure of a local community's revealed willingness to pay for wider beaches.

7.2 Cost-Benefit Analysis of Beach Nourishment

Setting aside any nonlinearities in the marginal benefits schedule, and ignoring the fact that only the repeat-sales coefficients are significantly different than zero, consider the following back-of-the-envelope calculations based on a literal interpretation of the point estimates from the results section. Table 12 presents the results of a simple break-even cost benefit analysis of the decision to nourish a section of beach. As the table shows, the differences-in-differences and repeat-sales point estimates indicate that willingness to pay for a one-foot beach nourishment project is between \$42 and \$68 (based on a \$500,000 home). This implies that a project that adds 70 feet of width to a beach would generate benefits of \$2,927 to \$4,760 per household. Since the cost of beach nourishment is roughly \$1,000,000 per mile, there would have to be between 210 and 342 beachfront homes per mile in order for the project to generate positive marginal benefits. Note, of course, that this simple break-even analysis ignores any benefits that beach nourishment may generate for non-beachfront properties or for the local economy (e.g., revenues from tourism).[8]

Point estimates based on the discontinuity matching procedure produce somewhat larger results (again, with the caveat that the numbers are not statistically distinguishable from zero). Assuming a decay rate of .91 and a constant of 16.5, the Markov regression results from Table 10 suggest that the average beach has a stable equilibrium of approximately 183 feet of width. For a nourishment project that adds 70 feet to the beach, the overall contribution to beach width during the first ten years (a typical nourishment interval) is 474 foot-years. At a marginal value of \$29 per foot-year, this implies that willingness to pay for a nourishment project is \$13,685 per household. A comparison against the \$1,000,000 per mile cost of nourishment implies that there would have to be 73 beachfront houses per mile of beach in order for a project to generate positive marginal benefits, based solely on benefits to coastal homeowners.

[8]To put these numbers in perspective, heavily developed areas (e.g., Miami Beach) with many high rise buildings might have over a thousand condos and apartments per mile of beach. Less developed areas might have fewer than fifty single-family homes.

7.3 Discussion

Overall, my results paint a picture that is both pessimistic and optimistic. On one hand, the results suggest that because homeowners have relatively low willingness to pay for wider beaches, the welfare costs of shoreline loss—and more broadly, of sea level rise—may not be as serious as believed. In particular, my results show that for a typical section of beach in the normal 100 to 400 foot range, changes in beach width have little impact on property values. However, the results also hint at the possibility that damages from shoreline loss are nonlinear. In particular, because houses located on very eroded beaches appear to experience substantial price discounts relative to homes on wider beaches, it appears possible that there may exist some threshold below which shoreline loss does have serious welfare effects. Because the statistical evidence for this claim is weak, further research is needed.

Additionally, it is important to interpret the overall results of this study in context. The general lack of price effects implies that changes in beach width do not affect coastal homeowners' appraisals of the recreational and use benefits from owning a beachfront home. However, because there are a variety of housing market inefficiencies that could weaken the relationship between prices and beach quality, it is possible that these revealed preference estimates are not an accurate measure of actual benefits. For example, homebuyers may choose homes based on long-term beach width, without taking advantage of the arbitrage opportunity to purchase "undervalued" homes that are experiencing wider than usual beach width. Alternatively, beach width may not be a salient characteristic at the time of home purchase, even though homebuyers would in fact derive more use benefits from a wider beach. Third, there may be negative externalities, such as crowding by members of the beachgoing public, that cancel out the benefits of wider beaches. Fourth, homebuyers may have unrealistic or overly optimistic beliefs about changes in beach width (e.g., even though I know that many beaches are eroding, I think the beach in front of my new home will accrete instead). Finally, the general equilibrium effects of widespread shoreline loss may be quite different than the partial equilibrium effects of specific beach nourishment projects—so that even if a beach nourishment project in a particular location has little effect on housing prices, the loss of shoreline along the entire Florida coast (as might be caused by sea level rise) could still have substantial price effects.

In respect to whether the results imply that homeowners do not value the storm protection benefits provided by wider beaches, the results are even less clear. At least two alternative explanations are possible. First, homebuyers may suffer from moral hazard, either because they have purchased insurance that reimburses them for storm-related damage, or because they believe that state and federal disaster relief programs will cover their losses. Second, homebuyers may suffer from myopia, in which the storm protection benefits from a wider beach are not a salient attribute at the time of purchase (Berger et al, 2009).

8 Conclusion

In this paper, I have developed a new "discontinuity matching" research design for estimating homeowners' marginal willingness to pay for time-variant neighborhood characteristics. I use this design, as well as traditional panel and differences-in-differences approaches, to estimate the welfare costs of shoreline loss along coastal beaches. In contrast to previous research that suggests that homeowners are willing to pay a substantial premium to live near wider beaches, I find that changes in beach width have little effect on the sale price of beachfront homes, except at very eroded beaches. The results suggest that policy interventions to prevent shoreline loss are most valuable near homes that are directly threatened by the ocean.

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Table 1: Examples of Major Beach Nourishment Projects

County	Beach	Year	Volume (cy, millions)	Length (miles)	Intensity (cy/ft)	Cost (millions)
Bay	Panama City Beach	1999	9.1	18.3	98	41.9
Brevard	Cape Canaveral-Cocoa Beach	2001	3.1	9.4	64	26.8
Brevard	South Reach Beach	2002	1.2	3.1	67	.
Broward	Broward County Segment III	2006	1.5	9.3	40	3.1
Broward	Hollywood-Hallandale	1991	1.1	5.1	40	14.3
Broward	Pompano Beach-Lauderdale by the Sea	1983	1.9	6.0	66	15.0
Dade	Sunny Isles	1988	1.3	2.6	88	27.9
Duval	Amelia Island	2002	1.9	5.1	96	9.4
Duval	Mayport-Kathryn Abby Hanna Park	1985	1.3	2.2	102	4.0
Escambia	Pensacola Beach	2003	4.2	8.2	96	23.0
Escambia	Pensacola Beach	2006	3.5	8.2	79	10.4
Escambia	Perdido Key	1985	2.4	1.2	520	9.9
Escambia	Perdido Key	1990	5.4	5.1	211	20.3
Lee	Captiva Island	1989	1.6	5.5	61	10.9
Lee	Captiva Island	1996	1.1	8.8	34	.
Lee	Captiva Island	2006	1.4	9.8	39	.
Manatee	Anna Maria Key	1993	2.3	4.6	92	19.3
Manatee	Anna Maria Key	2002	1.9	5.3	65	9.8
Martin	Jupiter Island	1983	1.0	7.8	26	5.1
Martin	Jupiter Island	1987	2.2	7.8	57	6.5
Martin	Jupiter Island	1996	1.7	5.5	64	9.7
Martin	Jupiter Island	2002	3.0	7.7	77	1.8
Martin	Jupiter Island	2007	2.3	7.3	62	.
Palm Beach	Boca Raton North	1988	1.1	1.5	129	6.3
Palm Beach	Delray Beach	1984	1.3	2.9	80	8.0
Palm Beach	Delray Beach	1992	1.2	1.6	123	7.3
Palm Beach	Delray Beach	2002	1.1	1.6	118	4.6
Palm Beach	Juno Beach	2001	1.0	3.4	72	13.2
Palm Beach	Midtown Beach	2003	1.4	10.2	93	.
Palm Beach	Palm Beach	1984	1.3	15.3	33	.
Palm Beach	Palm Beach	1992	1.2	15.1	30	6.0
Palm Beach	Phipps Ocean Park	2006	1.0	1.6	121	.
Pinellas	Sand Key	2006	1.3	6.9	34	23.4
Pinellas	Sand Key Phase II - Indian Rocks	1990	1.3	2.6	87	2.4
Pinellas	Sand Key Phase IV	1999	1.6	6.7	43	22.9
Sarasota	Longboat Key - multicounty	1993	3.1	12.8	63	27.3
St Johns	Anastasia State Park- St Augustine	2003	4.4	4.3	217	.
St Johns	Anastasia State Park- St Augustine	2005	2.8	2.9	185	14.1
St Johns	Duval County	1995	1.2	5.9	37	.
St Lucie	Martin County	1996	1.3	4.3	59	11.6

Note: This table presents basic characteristics for the 40 largest (by volume of sand placed on the beach) of the 204 beach nourishment projects included in the main analysis. Note that length is estimated from the length of shoreline covered by the FDEP survey markers affected by the nourishment project.

Table 2: Characteristics of Beach Nourishment Projects

	Mean	Std Dev	Minimum	Maximum	Observations
All Nourishments					
Year Completed	1996	7	1983	2007	204
Volume (cy, millions)	0.7	1.0	0.0	9.1	204
Length (miles)	3.8	3.8	0.2	19.4	204
Intensity (cy/ft)	47	51	0	520	204
Cost (millions)	6.6	8.1	0.0	41.9	127
Sales	62	130	0	1,473	204
Major Nourishments					
Year Completed	1997	7	1983	2007	94
Volume (cy, millions)	1.2	1.3	0.2	9.1	94
Length (miles)	4.2	3.5	1.0	18.3	94
Intensity (cy/ft)	75	60	25	520	94
Cost (millions)	9.8	8.6	0.9	41.9	68
Sales	72	172	0	1,473	94

Note: This table summarizes the characteristics of the set of beach nourishment projects included in the main analysis. The top panel includes all projects; the bottom panel includes only "major" nourishment projects covering 1 mile or more of beach, with nourishment intensity greater than or equal to 25 cubic yards per foot. In both panels, the sales variable represents the number of sales that occurred at properties within 20 meters of a nourished section of beach, in the year in which the beach was nourished. The observations variable represents the number of nourishment projects for which the selected variable is available.

Table 3: Summary Statistics

	Number of Major Nourishments per Monument		
	0	1 or 2	3 or more
Housing Characteristics			
Single Family	0.10 (0.00)	0.03*** (0.00)	0.09 (0.00)
Condo	0.90 (0.00)	0.97*** (0.00)	0.91 (0.00)
Vacant	0.18 (0.00)	0.02*** (0.00)	0.03*** (0.00)
Parcel Acreage	0.59 (0.01)	0.29*** (0.01)	1.35*** (0.02)
Housing Area (sq ft)	1,593 (12)	1,369*** (6)	1,701*** (24)
Bedrooms	1.94 (0.01)	1.62*** (0.01)	2.68*** (0.04)
Bathrooms	1.99 (0.01)	1.78*** (0.01)	2.45*** (0.04)
Year Renovated	1983.1 (0.1)	1982.0*** (0.1)	1999.2*** (0.2)
Year Built	1980.4 (0.1)	1978.3*** (0.1)	1981.4*** (0.2)
Structure Quality (1-6)	3.03 (0.01)	3.20*** (0.01)	3.21*** (0.02)
Brick Construction	0.12 (0.00)	0.09*** (0.00)	0.10*** (0.00)
Features Appraised Value	2,327 (219)	719*** (46)	5,209*** (402)
Distance to Beach (m)	1 (0)	1*** (0)	1*** (0)
Sales per Parcel	2.59 (0.01)	2.63*** (0.01)	2.77*** (0.01)
Sale Price (000s)	987 (15)	1,059*** (14)	538*** (15)
Beach Characteristics			
Beach Width (ft)	195.3 (1.0)	235.1*** (0.7)	197.0 (0.9)
Std Dev Beach Width (ft)	33.11 (0.36)	42.31*** (0.13)	56.84*** (0.41)
Nourishments	0.00 (0.00)	0.98*** (0.00)	2.69*** (0.01)
Cumulative Intensity (cy/ft)	0.00 (0.00)	56.58*** (0.29)	143.18*** (0.82)
Sales, by Time Period			
1983 to 1984	1,968	2,580	759
1985 to 1989	6,456	7,719	1,966
1990 to 1994	6,314	10,733	1,998
1995 to 1999	8,529	13,403	2,515
2000 to 2004	11,495	18,730	2,888
2005 to 2009	6,425	12,592	1,677
All years	41,187	65,757	11,803
Geographic Units			
Parcels	15,888	24,998	4,259
FDEP Survey Monuments	679	454	171
Six mile zones	51	45	18

Note: The "Housing Characteristics" panel presents mean unweighted parcel characteristics, with standard deviations in parentheses. The "Beach Characteristics" panel presents mean unweighted FDEP survey monument characteristics, with standard deviations in parentheses. The "Sales, by Time Period" panel presents the number of sales that occurred in each five-year period between 1980 and 2010. The "Geographic Units" panel describes the number of geographic units includes in the analysis. The columns represent the number of major nourishments (with intensity >25 cy/ft) at each FDEP survey monument. All t-tests are relative to the 0 nourishments group. * denotes p<.05; ** denotes p<.01; *** denotes p<.001.

Table 4: Housing Prices and Beach Width: Panel Results

	(1)		(2)		(3)		(4)	
Width: 0 ft	-0.045*	(0.022)	-0.054*	(0.024)	-0.019	(0.020)	-0.022	(0.019)
Width: 50 ft	-0.029	(0.017)	-0.032	(0.018)	-0.021	(0.013)	-0.007	(0.013)
Width: 100 ft	0.007	(0.014)	-0.004	(0.015)	-0.023*	(0.009)	-0.020	(0.010)
Width: 150 ft	-0.015	(0.013)	-0.019	(0.011)	-0.014	(0.008)	-0.010	(0.008)
Width: 250 ft	0.004	(0.015)	0.018	(0.017)	0.015	(0.013)	0.011	(0.012)
Width: 300 ft	0.066*	(0.030)	0.042	(0.030)	-0.012	(0.026)	-0.024	(0.028)
Width: 350 ft	0.014	(0.017)	0.010	(0.019)	-0.020	(0.035)	-0.037	(0.034)
Width: 400 ft	0.014	(0.032)	-0.005	(0.026)	0.011	(0.032)	0.002	(0.033)
Width: 450 ft	0.007	(0.049)	0.025	(0.066)	-0.009	(0.042)	-0.045	(0.046)
Width: 500 ft	-0.005	(0.049)	-0.014	(0.049)	-0.025	(0.044)	-0.044	(0.045)
Non-vacant	0.198***	(0.052)	0.130	(0.073)	0.175**	(0.053)	0.137*	(0.054)
Renovated	0.105**	(0.034)	0.150***	(0.040)	-0.020	(0.029)	0.013	(0.034)
Log Acreage	0.095*	(0.045)	0.087	(0.050)				
Total Area (sq ft)	0.000***	(0.000)	0.000***	(0.000)				
Bedrooms	0.103***	(0.012)	0.098***	(0.015)				
Bathrooms	-0.004	(0.018)	-0.007	(0.022)				
Effective Year Built	0.006***	(0.001)	0.007***	(0.002)				
Actual Year Built	0.002*	(0.001)	0.001	(0.001)				
Structure Quality (1-6)	0.007	(0.012)	0.007	(0.015)				
Brick Construction	-0.093***	(0.022)	-0.104***	(0.027)				
Extra Features Assessed Value	-0.000	(0.000)	-0.000	(0.000)				
Sales	57,199		23,547		23,547		23,547	
Clusters	64		64		64		64	
R-squared	0.779		0.792		0.629		0.582	
Year-Area FE	No		No		No		Yes	
Year-County FE	Yes		Yes		Yes		No	
Year-Housing Type FE	Yes		Yes		Yes		No	
County FE	Yes		Yes		No		No	
Parcel FE	No		No		Yes		Yes	
Repeat Sales Only	No		Yes		Yes		Yes	

Note: This table presents coefficients and standard errors from a regression of log sales price on beach width. Column (1) shows a conventional hedonic analysis based on all available sales transactions, and Column (2) shows a conventional hedonic analysis based only on sales at houses with two or more sales. Columns (3) and (4) show results from a fixed-effects repeat-sales analysis corresponding to equation (11). In all specifications, each observation represents a unique housing sale between 1983 and 2009, for which beach width data was available, at a house within 20 meters of the beach. Standard errors are clustered by six-mile zone, and regressions are weighted at the same level. * denotes p<.05; ** denotes p<.01; *** denotes p<.001.

Table 5: Characteristics of Properties Sold in Years Before and After Nourishment

	Two Years Before	One Year Before	Year of Nourishment	One Year After
Condo	0.68 (0.03)	0.69 (0.03)	0.69 (0.03)	0.69 (0.03)
Parcel Acreage	0.63 (0.07)	0.60 (0.08)	0.59 (0.07)	0.66 (0.08)
Housing Area (sq ft)	2,555 (161)	2,424 (145)	2,385 (152)	2,698 (194)
Bedrooms	1.56 (0.10)	1.46 (0.10)	1.42 (0.09)	1.47 (0.09)
Bathrooms	1.22 (0.09)	1.13 (0.09)	1.11 (0.09)	1.14 (0.09)
Year Renovated	1987.0 (0.8)	1986.5 (0.9)	1986.9 (0.8)	1986.7 (0.9)
Year Built	1979.8 (0.8)	1979.1 (0.9)	1978.8 (0.9)	1979.9 (0.8)
Structure Quality (1-6)	3.41 (0.07)	3.35 (0.07)	3.33 (0.07)	3.33 (0.07)
Brick Construction	0.21 (0.02)	0.22 (0.02)	0.21 (0.02)	0.22 (0.02)
Features Appraised Value	15,556 (2,951)	9,782 (1,715)	24,802 (12,771)	17,789* (3,406)
Sale Price (000s)	685 (132)	745 (160)	844 (169)	779 (144)
Beach Width (ft)	199 (9)	180 (7)	261*** (7)	250*** (7)
Major Nourishments	0.02** (0.01)	0.00 (0.00)	1.00 (0.00)	0.00 (0.00)
Intensity (cy/ft)	2.97* (1.24)	0.34 (0.13)	56.70*** (1.62)	0.34 (0.14)
neighborhoods	294	303	317	317

Note: This table shows means and standard errors of the characteristics of properties sold in the years before and after beach nourishment, for properties located within 20 meters of the beach. The table includes pre and post data for each nourishment project with intensity greater than 25 cy/ft. Each observation represents the mean characteristics for a one-mile neighborhood in a particular year. The t-tests are based on unpaired, two-tailed comparisons, relative to the one year before nourishment category. * denotes p<.05; ** denotes p<.01; *** denotes p<.001.

Table 6: Beach Width and Nourishment

	(1)	
Nourishment, 5 years before	-4.08	(7.35)
Nourishment, 4 years before	-22.75**	(6.60)
Nourishment, 3 years before	-12.58*	(6.11)
Nourishment, 2 years before	-19.54**	(6.27)
Nourishment, 1 year before	-38.28***	(6.77)
Nourishment	45.43***	(4.83)
Nourishment, 1 year after	31.32***	(4.35)
Nourishment, 2 years after	17.82***	(4.25)
Nourishment, 3 years after	17.86**	(6.02)
Nourishment, 4 years after	21.49**	(7.65)
Observations	34,243	
Clusters	61	
R-squared	0.149	
Elapsed Year-Base Year FE	Yes	
Elapsed Year-Location FE	Yes	

Note: This table presents coefficients and standard errors from the differences-in-differences regression corresponding to equation (15). The dependent variable is beach width, in feet. Each observation represents a unique one-mile neighborhood and year between 1983 and 2009, for which beach width data was available. Standard errors are clustered by six-mile zone, and regressions are weighted at the same level. * denotes p<.05; ** denotes p<.01; *** denotes p<.001.

Table 7: Beach Width and Nourishment, by Nourishment Intensity

	(1)	
25-49 cy/ft, 5 years before	1	(10)
25-49 cy/ft, 4 years before	-6	(7)
25-49 cy/ft, 3 years before	-1	(7)
25-49 cy/ft, 2 years before	-4	(7)
25-49 cy/ft, 1 year before	-20*	(9)
25-49 cy/ft	37***	(5)
25-49 cy/ft, 1 year after	20**	(6)
25-49 cy/ft, 2 years after	3	(6)
25-49 cy/ft, 3 years after	3	(7)
25-49 cy/ft, 4 years after	25**	(8)
50-74 cy/ft, 5 years before	-13	(10)
50-74 cy/ft, 4 years before	-28*	(11)
50-74 cy/ft, 3 years before	-13	(9)
50-74 cy/ft, 2 years before	-38***	(6)
50-74 cy/ft, 1 year before	-53***	(10)
50-74 cy/ft	40***	(8)
50-74 cy/ft, 1 year after	22**	(7)
50-74 cy/ft, 2 years after	14*	(5)
50-74 cy/ft, 3 years after	12	(7)
50-74 cy/ft, 4 years after	8	(11)
75-up cy/ft, 5 years before	-8	(11)
75-up cy/ft, 4 years before	-39***	(11)
75-up cy/ft, 3 years before	-29*	(14)
75-up cy/ft, 2 years before	-27	(22)
75-up cy/ft, 1 year before	-54***	(10)
75-up cy/ft	67***	(8)
75-up cy/ft, 1 year after	57***	(6)
75-up cy/ft, 2 years after	42***	(7)
75-up cy/ft, 3 years after	36*	(14)
75-up cy/ft, 4 years after	32	(17)
Observations	34,243	
Clusters	61	
R-squared	0.157	
Elapsed Year-Base Year FE	Yes	
Elapsed Year-Location FE	Yes	

Note: This table presents coefficients and standard errors from differences-in-differences regression corresponding to equation (15), where the effects of nourishment are disaggregated by intensity into four categories: 1-24 cy/ft, 25-49 cy/ft, 50-74 cy/ft, and $\geq$75 cy/ft. The dependent variable is beach width, in feet. Each observation represents a unique one-mile neighborhood and year between 1983 and 2009, for which beach width data was available. Standard errors are clustered by six-mile zone, and regressions are weighted at the same level. * denotes $p<.05$; ** denotes $p<.01$; *** denotes $p<.001$.

Table 8: Housing Prices and Nourishment: Differences-in-Differences Results

	0-19 m	20-799 m	800-5000 m
Nourishment, 5 years before	-0.019*	-0.014	-0.019
	(0.008)	(0.008)	(0.012)
Nourishment, 4 years before	-0.011	-0.017*	-0.018**
	(0.010)	(0.007)	(0.006)
Nourishment, 3 years before	-0.011	-0.013*	0.009
	(0.008)	(0.006)	(0.020)
Nourishment, 2 years before	-0.019	-0.015	0.008
	(0.014)	(0.008)	(0.017)
Nourishment, 1 year before	-0.023*	-0.005	-0.008
	(0.010)	(0.009)	(0.008)
Nourishment	-0.016	-0.011	0.001
	(0.011)	(0.007)	(0.012)
Nourishment, 1 year after	-0.007	-0.017**	0.010
	(0.012)	(0.006)	(0.014)
Nourishment, 2 years after	0.000	-0.017*	0.000
	(0.010)	(0.007)	(0.009)
Nourishment, 3 years after	0.004	-0.001	0.005
	(0.012)	(0.007)	(0.011)
Nourishment, 4 years after	0.011	0.002	0.010
	(0.008)	(0.007)	(0.011)
Observations	65,071	81,462	82,006
Clusters	61	67	65
R-squared	0.534	0.659	0.468
Elapsed Year-Base Year FE	Yes	Yes	Yes
Elapsed Year-Location FE	Yes	Yes	Yes

Note: This table presents coefficients and standard errors from the differences-in-differences regression corresponding to equation (14). The dependent variable is the log of the sale price index for properties located within 20 meters of the beach. Each observation represents a unique one-mile neighborhood and year between 1983 and 2009. Standard errors are clustered by six-mile zone, and regressions are weighted at the same level. * denotes p<.05; ** denotes p<.01; *** denotes p<.001.

Table 9: Housing Prices and Nourishment: Differences-in-Differences Results by Intensity

	0-19 m		20-799 m		800-5000 m	
25-49 cy/ft, 5 years before	-0.025	(0.013)	-0.012	(0.010)	-0.009	(0.007)
25-49 cy/ft, 4 years before	-0.024*	(0.011)	-0.017	(0.014)	-0.018*	(0.008)
25-49 cy/ft, 3 years before	-0.031**	(0.010)	-0.023**	(0.008)	-0.022*	(0.009)
25-49 cy/ft, 2 years before	-0.011	(0.013)	0.002	(0.011)	-0.016	(0.010)
25-49 cy/ft, 1 year before	-0.017	(0.012)	0.002	(0.010)	-0.004	(0.008)
25-49 cy/ft	-0.011	(0.020)	-0.015	(0.012)	-0.021*	(0.010)
25-49 cy/ft, 1 year after	-0.003	(0.019)	-0.018*	(0.008)	-0.011	(0.008)
25-49 cy/ft, 2 years after	-0.000	(0.015)	-0.017	(0.010)	-0.001	(0.008)
25-49 cy/ft, 3 years after	0.012	(0.017)	0.008	(0.013)	-0.011	(0.008)
25-49 cy/ft, 4 years after	0.020	(0.012)	0.017	(0.013)	0.004	(0.008)
50-74 cy/ft, 5 years before	-0.004	(0.020)	0.001	(0.009)	0.005	(0.009)
50-74 cy/ft, 4 years before	-0.023	(0.018)	-0.006	(0.008)	-0.015	(0.010)
50-74 cy/ft, 3 years before	0.006	(0.012)	0.002	(0.010)	-0.014	(0.009)
50-74 cy/ft, 2 years before	-0.035	(0.022)	-0.031*	(0.015)	-0.006	(0.008)
50-74 cy/ft, 1 year before	-0.039*	(0.016)	-0.003	(0.020)	-0.007	(0.009)
50-74 cy/ft	-0.023	(0.012)	-0.005	(0.011)	-0.019*	(0.010)
50-74 cy/ft, 1 year after	-0.023	(0.015)	-0.013	(0.011)	-0.016	(0.014)
50-74 cy/ft, 2 years after	0.006	(0.017)	-0.015	(0.011)	-0.029	(0.014)
50-74 cy/ft, 3 years after	-0.007	(0.014)	0.000	(0.011)	-0.008	(0.009)
50-74 cy/ft, 4 years after	0.008	(0.015)	-0.005	(0.012)	-0.013	(0.016)
75-up cy/ft, 5 years before	-0.018	(0.017)	-0.009	(0.013)	-0.004	(0.020)
75-up cy/ft, 4 years before	0.037	(0.025)	-0.023	(0.014)	-0.000	(0.012)
75-up cy/ft, 3 years before	0.005	(0.023)	-0.005	(0.011)	0.010	(0.014)
75-up cy/ft, 2 years before	0.027	(0.021)	-0.013	(0.016)	-0.001	(0.014)
75-up cy/ft, 1 year before	-0.005	(0.019)	0.002	(0.009)	0.010	(0.018)
75-up cy/ft	0.001	(0.019)	0.004	(0.016)	0.020*	(0.008)
75-up cy/ft, 1 year after	-0.004	(0.021)	-0.014	(0.013)	0.015	(0.011)
75-up cy/ft, 2 years after	-0.024*	(0.011)	-0.017	(0.011)	-0.001	(0.011)
75-up cy/ft, 3 years after	-0.008	(0.026)	-0.019*	(0.009)	-0.012	(0.016)
75-up cy/ft, 4 years after	-0.007	(0.017)	-0.024	(0.018)	-0.013	(0.020)
Observations	65,071		81,462		82,006	
Clusters	61		67		65	
R-squared	0.530		0.660		0.496	
Elapsed Year-Base Year FE	Yes		Yes		Yes	
Elapsed Year-Location FE	Yes		Yes		Yes	

Note: This table presents coefficients and standard errors from the differences-in-differences regression corresponding to equation (14), where the effects of nourishment are disaggregated by intensity into four categories: 1-24 cy/ft, 25-49 cy/ft, 50-74 cy/ft, and $\geq$75 cy/ft.. The dependent variable is the log of the sale price index for properties located within 20 meters of the beach. Each observation represents a unique one-mile neighborhood and year between 1983 and 2009. Standard errors are clustered by six-mile zone, and regressions are weighted at the same level. * denotes p<.05; ** denotes p<.01; *** denotes p<.001.

Table 10: Beach Width Markov Regression Results

	(1)	(2A)	(2B)	(2C)	(2D)	(2E)
Width, year -1	0.91***	0.93***	0.91***	0.92***	0.82***	0.88***
	(0.02)	(0.01)	(0.03)	(0.03)	(0.03)	(0.02)
Major Nourishment	66.44***	68.00***	87.00***	59.53***	41.14	37.29**
	(6.62)	(16.80)	(10.16)	(4.69)	(17.21)	(7.97)
Constant	16.62***	15.12***	15.51**	15.98**	40.38**	27.08*
	(3.21)	(2.68)	(5.01)	(4.65)	(6.70)	(7.50)
Observations	4,342	1,534	1,820	572	156	260
Clusters	50	33	30	12	4	6
R-squared	0.850	0.880	0.834	0.840	0.689	0.810

Note: This table presents the coefficients from estimating equation (17), with standard errors in parentheses. The dependent variable is current beach width, in feet. Column (1) includes all observations. Columns (2A) through (2E) include the set of beaches that are nourished 1, 2, 3, 4, or 5 times, respectively, during the period from 1983 to 2009. In all models, standard errors are clustered by six-mile zones. * denotes $p<.05$; ** denotes $p<.01$; *** denotes $p<.001$.

Table 11: Discontinuity Matching Results

Outcome	Coefficient	Std Err	95% Confidence Interval	
PATT, width	-60	4	-67	-53
PATT, sale price	-1,729	8,808	-18,992	15,535
$\partial P/\partial w$	29	.	.	.

Note: This table presents nearest neighbor matching results corresponding to Equations (21) and (24). Each observation represents a unique one-mile neighborhood and year. Unobserved potential outcomes for nourished beaches are estimated using the 6 closest unnourished observations. The vector of match variables includes predicted next-period beach width, year, and the total number of nourishments occuring at each beach. Matching is exact on the year variable, and the standard errors are robust. The table also shows the result of estimating Equation (25). To avoid being misleading, standard errors and confidence intervals are not shown for this estimate, which represents the ratio of two random variables with an unknown degree of correlation. The figure is based on the set of housing transactions at properties located within 20 meters of the beach.

Table 12: Willingness to Pay for Wider Beaches

Research Design	WTP metric	$\partial P/\partial w$	Value of 70 foot nourishment	Break-even HH per mile
Repeat Sales, <250 feet	One foot nourishment	\$68	\$4,760	210
Differences-in-Differences	One foot nourishment	\$42	\$2,927	342
Discontinuity Matching	One foot rental	\$29	\$13,685	73

Note: The table summarizes point estimates of willingness to pay for wider beaches based on the three research designs. The "WTP metric" column describes the correct welfare interepretation of each estimate of $\partial P/\partial w$. These calculations are based on a \$500,000 home. The "Value of 70 foot nourishment" column presents an estimate of the value per household of a 70 foot beach nourishment. For the discontinuity matching estimates, this nourishment is assumed to have a lifetime of 10 years, during which beach width decays following the model presented in Table 10. The "Break-even HH per mile" column describes the number of households that would have to be located on a one-mile section of beach in order for the marginal benefits of nourishment to exceed the \$1,000,000 nourishment cost per mile. Note that this break-even analysis does not consider other contributions that beach nourishment makes to local economies. Also note that the results apply only to properties located within 20 meters of the beach. Finally, note that these calculations are based on point estimates, and that 95 percent confidence intervals are consistent with a broader range of possible willingness-to-pay values.

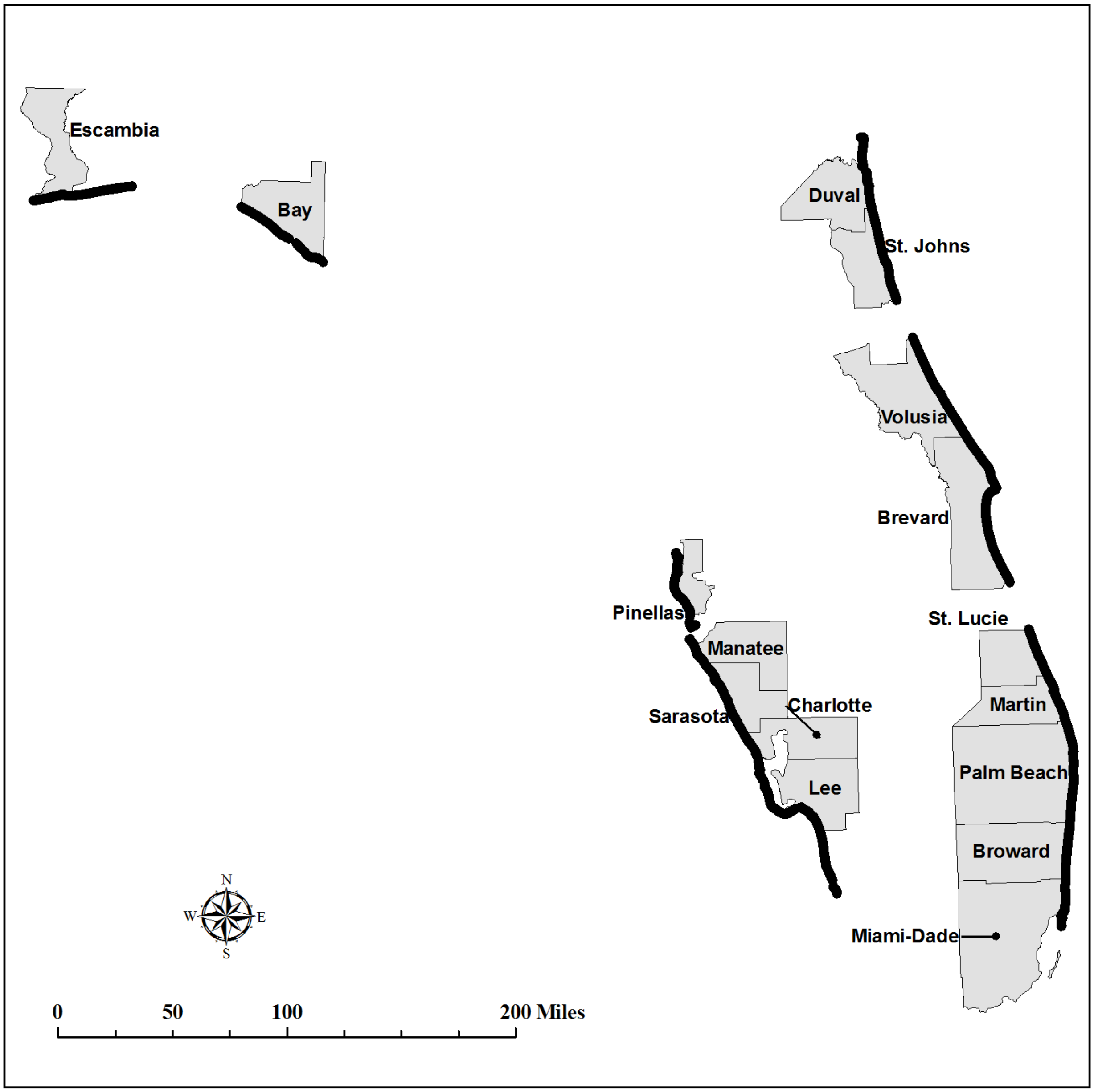

Figure 1: Map of the Study Area

Note: The thick solid line denotes areas where coastal mean high water (MHW) line survey data is available from the Florida Department of Environmental Protection. Grey shaded areas represent the sixteen in-sample individual counties.

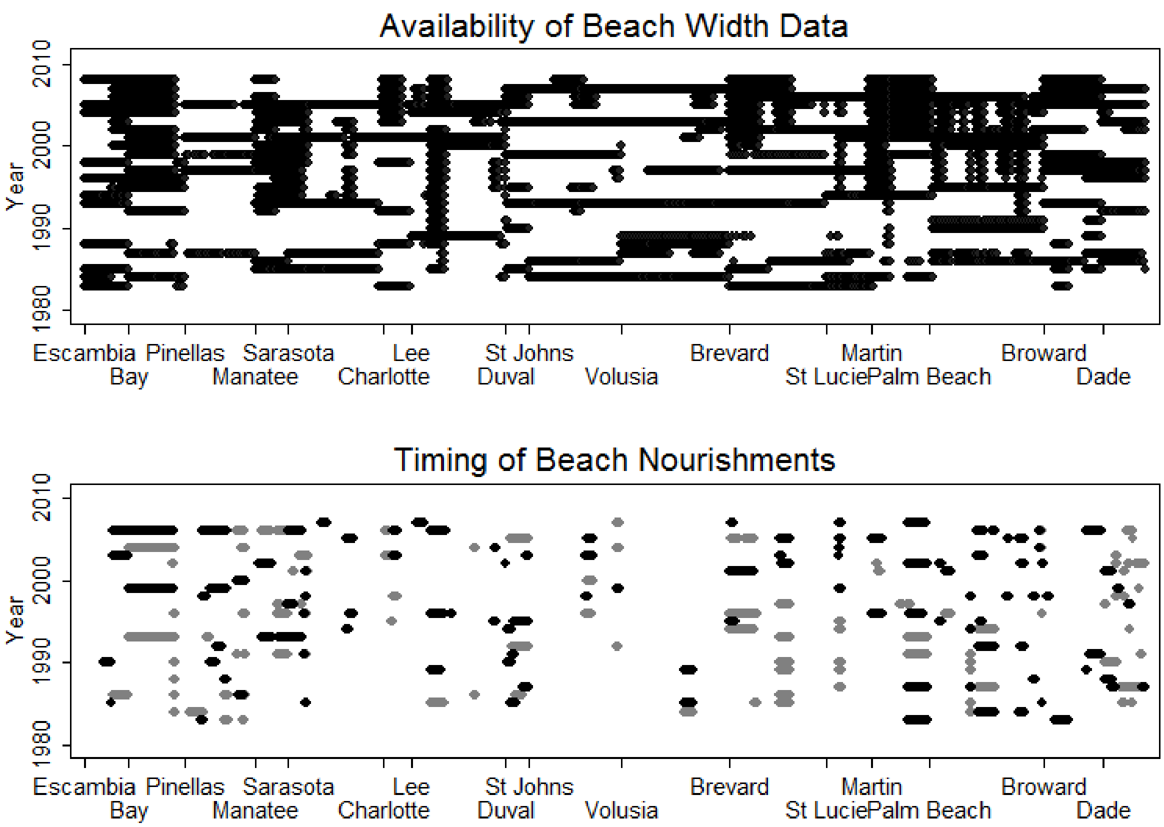

Figure 2: Location and Timing of Surveys and Nourishment Projects

Note: The upper panel shows the availability of beach width survey data, by year and location along the coast. The lower panel shows the timing of beach nourishment projects, by year and location. Major beach nourishment projects are shown in black; minor projects are shown in grey. Each point on the x-axis represents a unique coastal survey monument (in most areas, monuments are spaced approximately 1000 feet apart along the coast). To construct this figure, monuments were ordered from north to south along Florida's Gulf coast, and then from north to south along Florida's Atlantic coast. The x-axis should not be interpreted as a measure of absolute distance, only of relative location. As shown in Figure 1, survey coverage of Florida's coastline is incomplete.

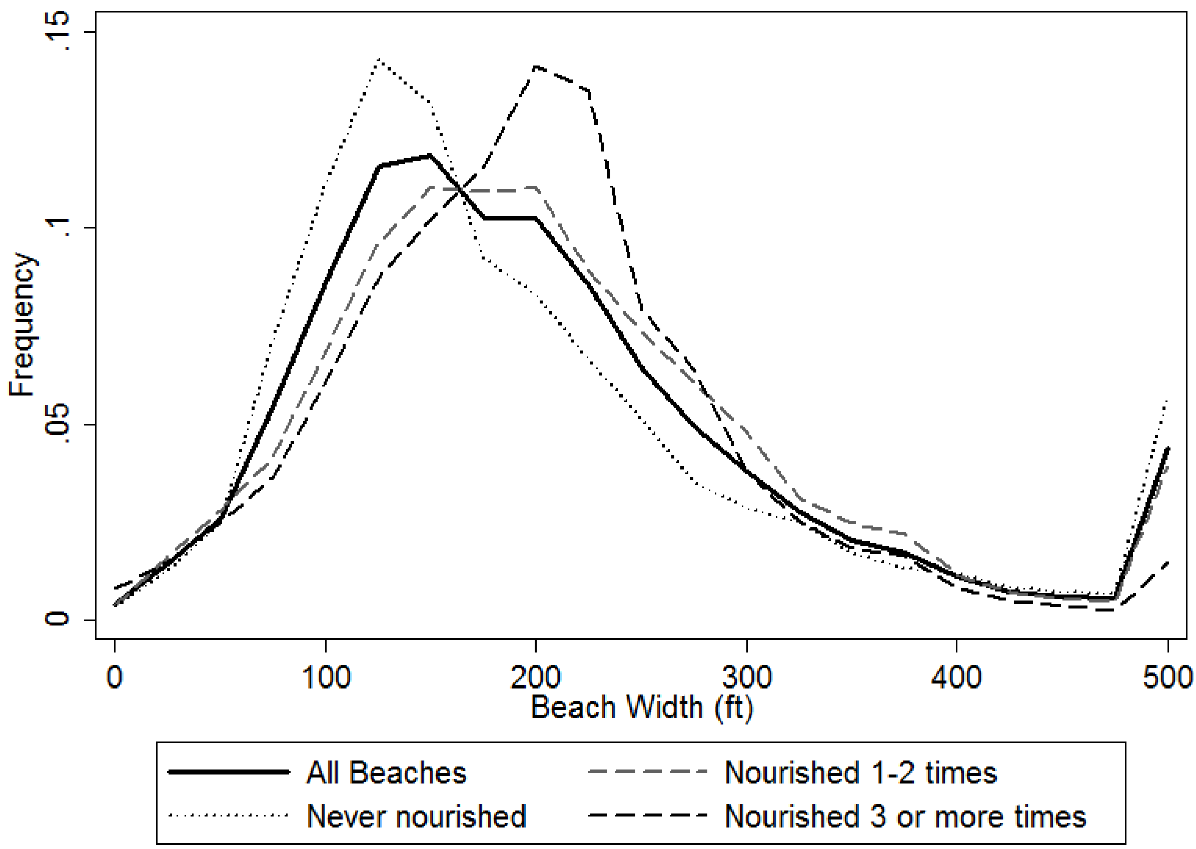

Figure 3: Distribution of Beach Width, by Nourishment Frequency
Note: This figure shows histograms of beach width, for all beaches, and by nourishment frequency. Beach widths greater than 500 ft are shown at 500 ft. Each observation represents a unique survey monument and year. The figure includes data from 1983 to 2009 for all in-sample counties.

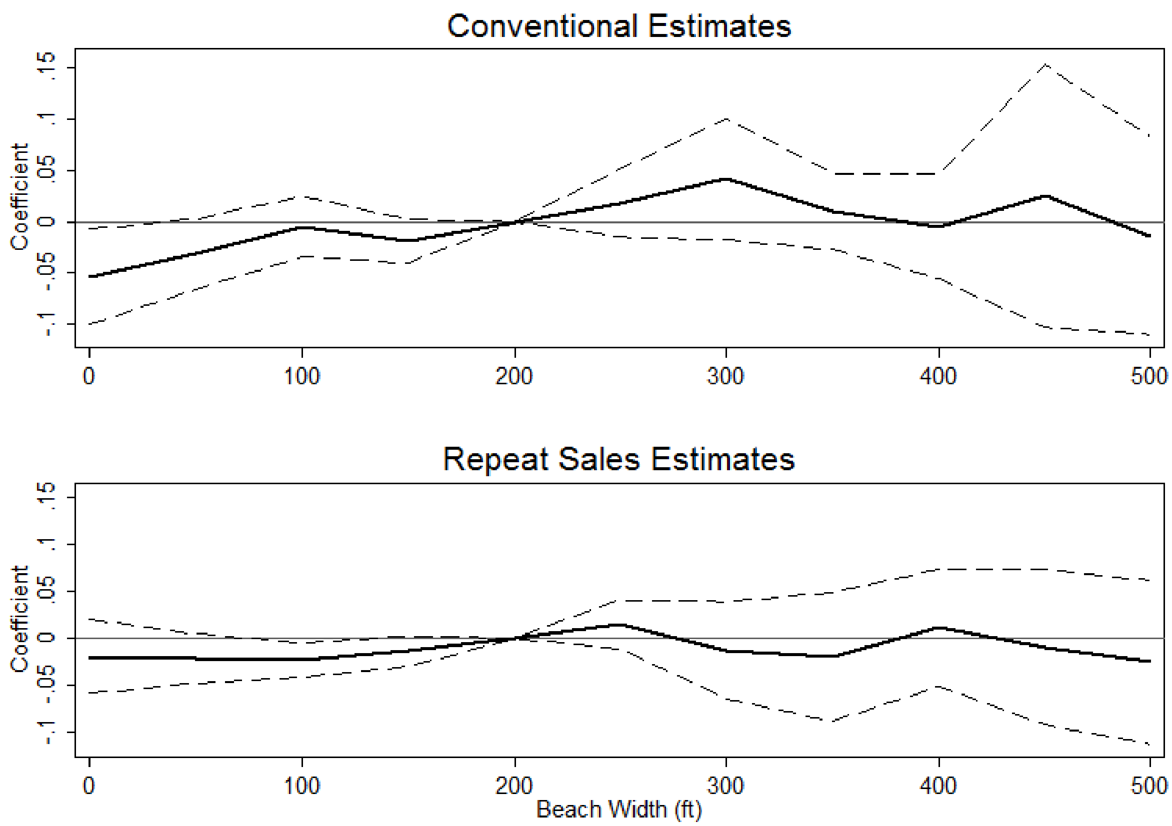

Figure 4: Panel Regression Results: Capitalized Price Versus Beach Width

Note: This figure plots coefficients and 95 percent confidence intervals from Table 4. The top panel presents the conventional OLS hedonic estimates from Column (2) of Table 4, and bottom panel presents the repeat-sales estimates from Column (3). The dependent variable in both specifications is log sales price. The omitted width category is 200 feet. The figure is based on the set of housing transactions at properties located within 20 meters of the beach.

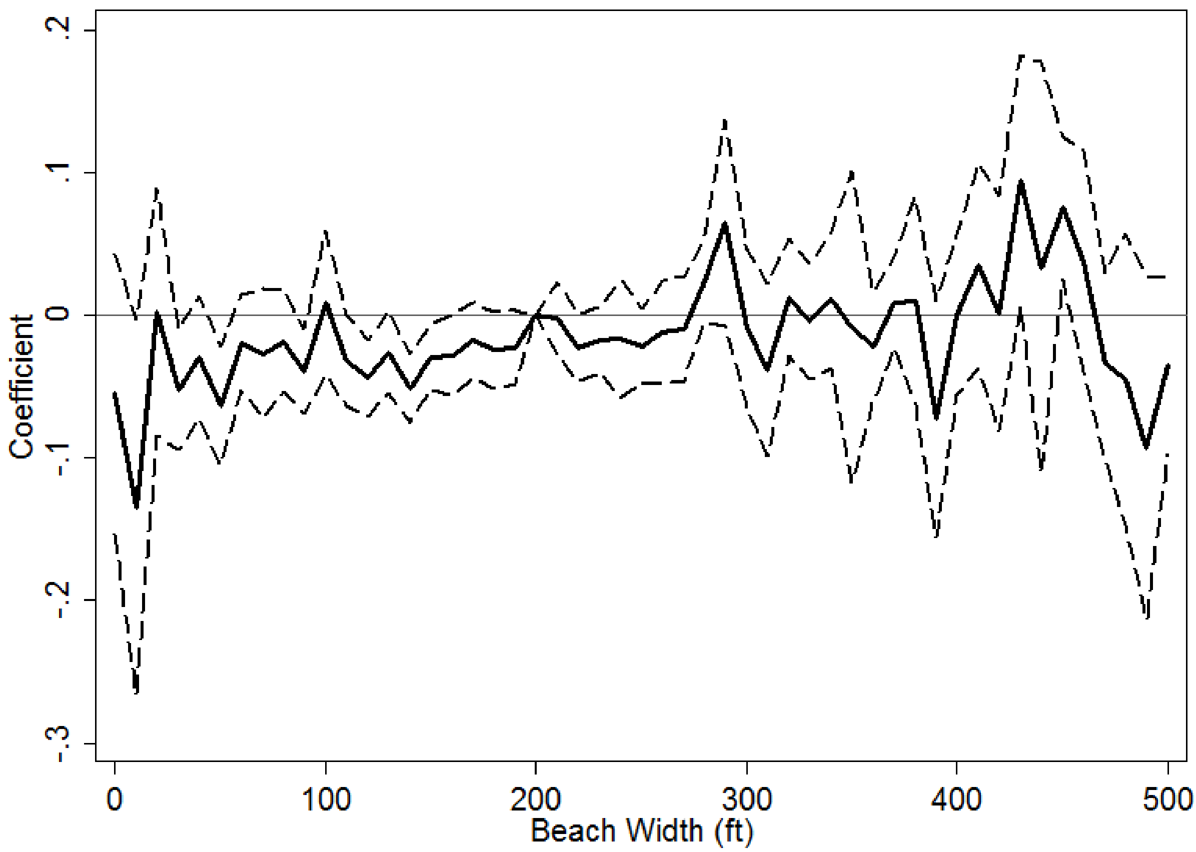

Figure 5: Panel Regression Results: Capitalized Price Versus Beach Width, with Detail
Note: This figure plots coefficients and 95 percent confidence intervals for a repeat sales regression similar to Equation (11), but with the beach width variable divided into 10 foot bins. The dependent variable is log sales price, and the figure is based on the set of housing transactions at properties located within 20 meters of the beach. The omitted width category is 200 feet.

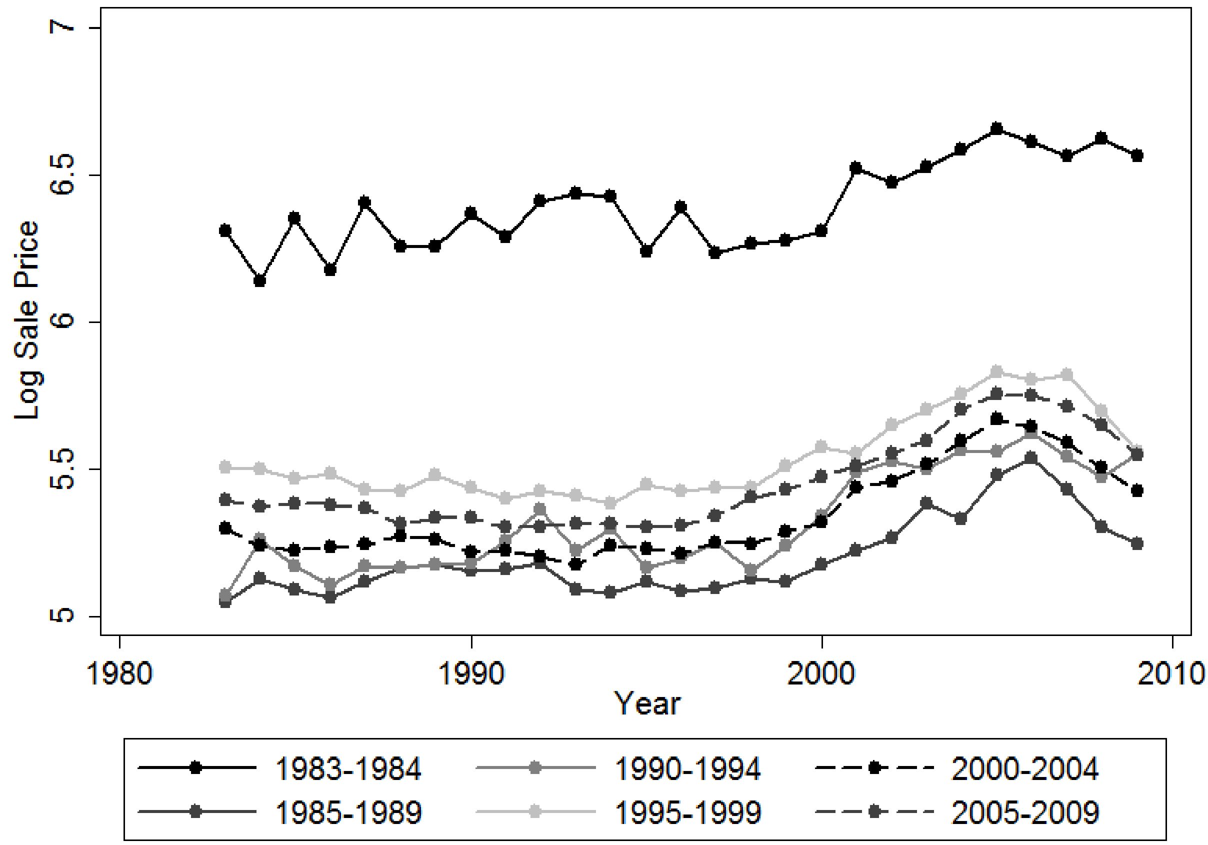

Figure 6: Trend in Sales Price, by Year of Most Recent Nourishment

Note: The figure plots mean log sale price over time for properties located within 20 meters of the beach, by the five-year period in which the beach near each survey monument was last nourished. Means are calculated across all one-mile neighborhood-by-year observations. The figure excludes areas that were not nourished between 1983 and 2009.

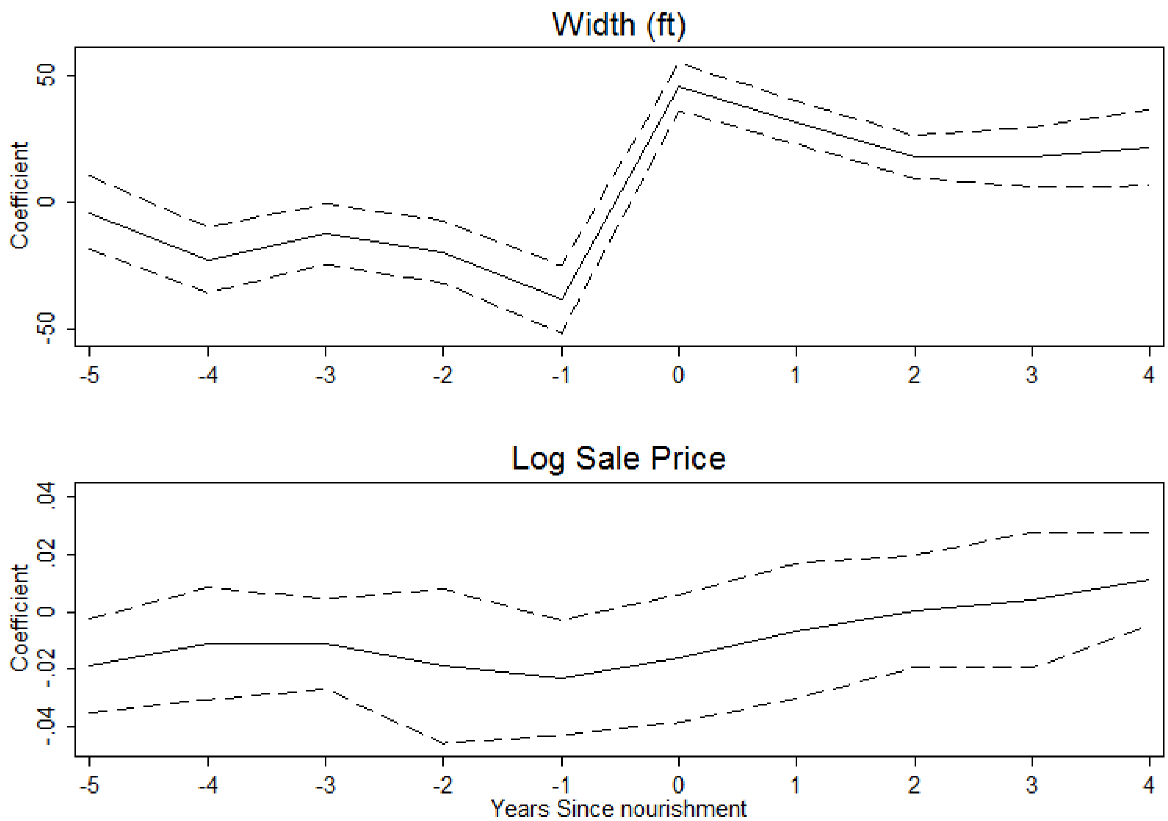

Figure 7: Differences-in-Differences Results

Note: The top panel plots 95 percent confidence intervals for the differences-in-differences coefficients from Table 6. The dependent variable is beach width in feet. The bottom panel plots confidence intervals for the differences-in-differences coefficients from Table 8. The dependent variable is log sales price. The shared x-axis represents the number of years since nourishment, where nourishment occurs in year 0. The figure is based on the set of properties located within 20 meters of the upper end of the beach.

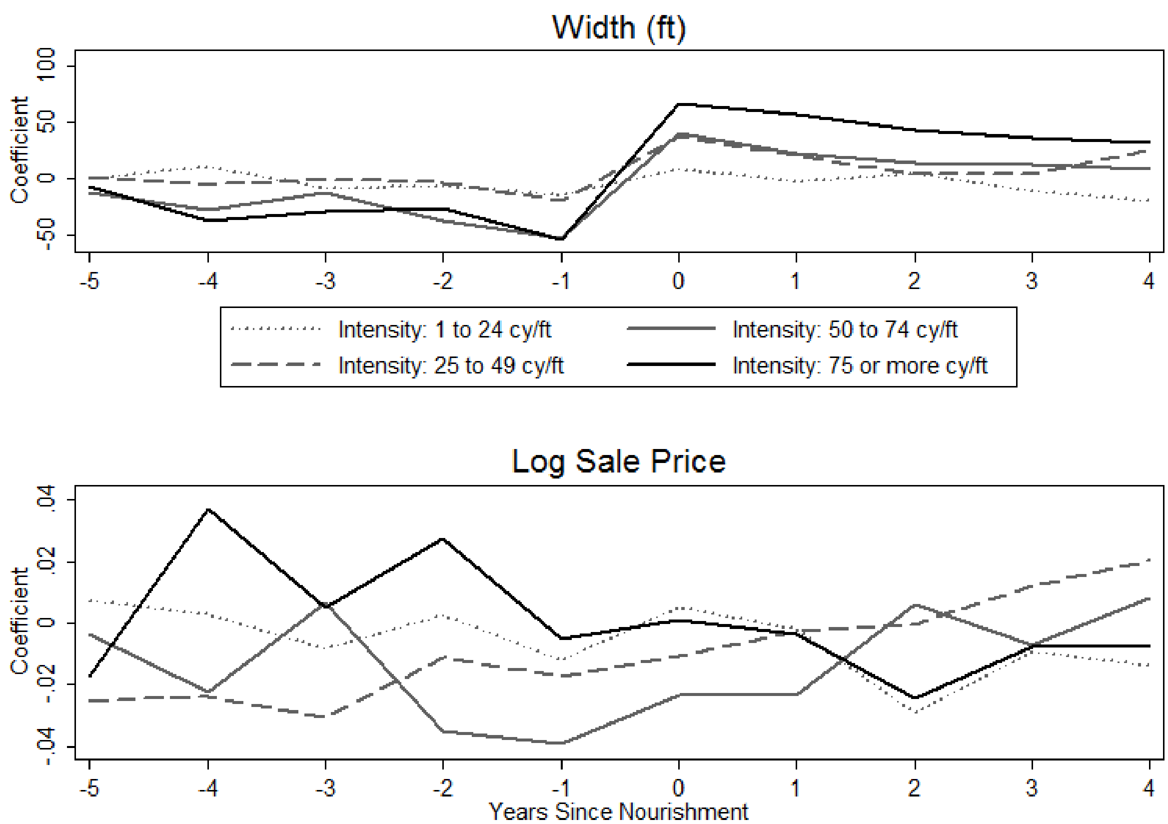

Figure 8: Differences-in-Differences Results by Nourishment Intensity

Note: The top panel plots the differences-in-differences coefficients from Table 7. The dependent variable is beach width in feet. The bottom panel plots the differences-in-differences coefficients from Table 9. The dependent variable is log sales price index for houses located within 20 meters of the beach. The shared x-axis represents the number of years since nourishment, where nourishment occurs in year 0. The intensity categories represent the quantity of sand placed on the beach, in cubic yards, per foot of shoreline. Both panels present coefficients relative to sections of beach that are not nourished in year 0.

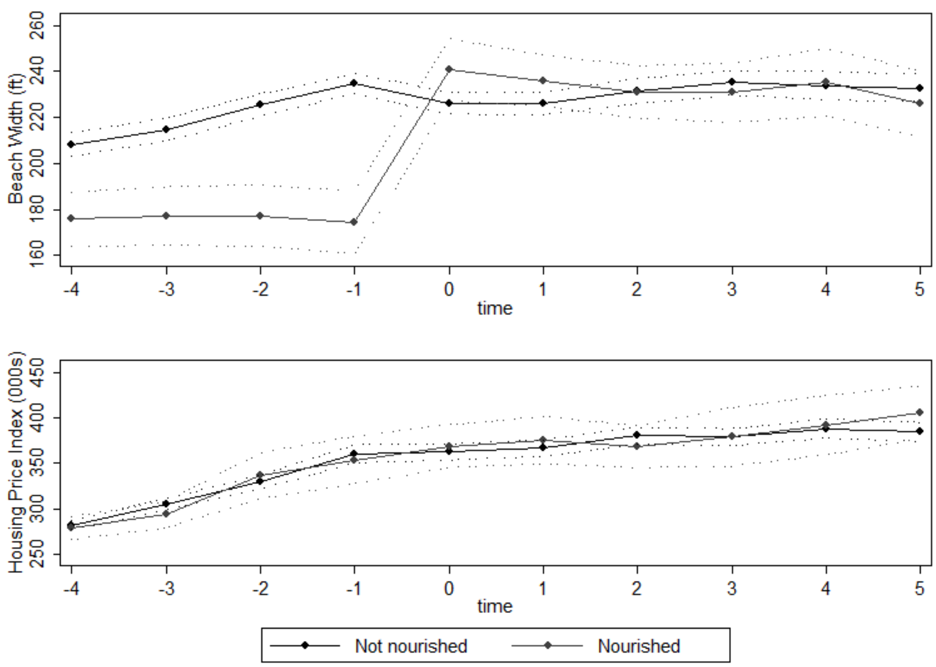

Figure 9: Discontinuity Matching Results: Trends in Width and Price

Note: This figure shows trends in the outcome variable for the treatment and control groups for the discontinuity matching procedure. In both panels, the treatment variable is nourishment in elapsed year 0, and the matching variable is predicted width in elapsed year 0, based on information available in year -1. The upper panel shows actual width and the lower panel shows the actual price index for properties located within 20 meters of the beach.