Understanding Trade-Offs between Built and Natural Assets in Coastal Management Projects for Inland, Coastal Residents using Latent Class Modeling Techniques: An Application to the Connecticut Coastline

Julia Karen Dumaine

B.S., University of Connecticut, 2015

A Thesis

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Master of Science

At the

University of Connecticut

2019

APPROVAL PAGE

Master of Science Thesis

Understanding Trade-Offs between Built and Natural Assets in Coastal Management Projects for Inland, Coastal Residents using Latent Class Modeling Techniques: An Application to the Connecticut Coastline

Presented by

Julia Karen Dumaine, B.S.

Major Advisor____

Stephen Swallow

Associate Advisor____

Charles Towe

Associate Advisor____

Juliana Barrett

University of Connecticut

2019

Acknowledgements

The author would like to thank and acknowledge the following advisors for their contributions to the project:

Dr. Stephen Swallow, Department of Agriculture and Resource Economics, University of Connecticut

Dr. Juliana Barrett, Connecticut Sea Grant College Program, University of Connecticut

Dr. James O'Donnell, Department of Marine Sciences, University of Connecticut

Dr. Christopher Elphick, Department of Ecology & Evolutionary Biology, University of Connecticut

Dr. Eric Schulz, Department of Ecology & Evolutionary Biology, University of Connecticut

Dr. Jennifer O'Donnell, Department of Marine Sciences, University of Connecticut

Alicia Barriga, Ph.D. Student, Department of Agriculture and Resource Economics, University of Connecticut

Gabriel Marmolejos, Ph.D. Student., Department of Agriculture and Resource Economics, University of Connecticut

The author is also grateful for grant support from the Connecticut Sea Grant College Program at the University of Connecticut as well as the Connecticut Institute for Resilience and Climate Adaptation (CIRCA).

Grant Number: R/CA-1

Sea Grant Award Number: NA14OAR4170086, with matching funds from CIRCA

Table of Contents

Abstract

Climate change threatens our established communities worldwide through consistently increased average surface temperatures, rising sea levels, and precipitation extremes, and Connecticut is no exception (U.S. Global Change Research Program 2017). As coastal communities in Connecticut increase their focus on mitigating the effects of climate change, they are not always able to incorporate town residents' preferences and values into their planning; particularly those residents who may not receive a direct benefit from the plan of which they contribute tax dollars towards. Our study attempts to estimate these preferences and values by using a choice experiment survey distributed across the Connecticut coastline which compares various coastal management plans and their outcomes. We use the survey's results to estimate how public support for a coastal management plan is affected by a plan's impacts on natural and built assets, and by respondents' geographic location along the Connecticut coastline. Additionally, we employ Latent Class Modeling which groups respondents by their underlying preferences in order to further evaluate how respondents' unobservable characteristics affect their choice of a coastal management plan.

1 Introduction

1.1 Background

For centuries, coastal lands have been a core asset in the establishment of many of the world's most successful economies, leading humans to rely on coastlines for settlement, recreation, environmental resources, trade and commerce, power generation, military, and more (Weinstein, et al., 2007). Today however, climate change threatens our established communities worldwide through consistently increased average surface temperatures, rising sea levels, and precipitation extremes, and Connecticut is no exception (U.S. Global Change Research Program 2017). Sea level rise (SLR) projections for Connecticut range from one to two and a half feet by the 2050's and with nearly 30 percent of the state's population living in Connecticut's 24 Long Island Sound-bordering towns (U.S. Census Bureau, 2019; O'Donnell, 2018) there is significant need to 3respond to these predictions.

The most significant risk that SLR poses to these communities is through increased storm surges. Storm surges, which are defined as "abnormally high waters generated by severe storms such as hurricanes, cyclones, and nor'easters," are predicted to be an average of eight inches higher than in 1900 by 2100, exaggerating the damage caused by extreme weather (U.S. Climate Resilience Toolkit, 2017). Since 2005, there have been sixteen federally declared disasters in Connecticut that have cost the Federal Emergency Management Agency (FEMA) over $281 million in public funds (FEMA, 2018).[1] The Connecticut Department of Transportation reported over $63 million in state infrastructure fiscal impacts related to severe storms and hurricanes between 2010 and 2012 (Connecticut Department of Energy and Environmental Protection, 2014). Additionally, the National Oceanic and Atmospheric Administration's (NOAA's) National Climatic Data

[1] This does not represent the total cost of damages caused by federally-declared disasters in Connecticut.

Center tracks impacts of severe weather events in Connecticut and has reported over $1.6 billion in property damages since tracking began in 1955.

Traditionally, coastal communities have opted to construct hard coastal defense mechanisms, often referred to as "armoring", to protect built assets from storm damage (Schlacher, et al., 2007). However, in 2012, Connecticut modified its statutes to place increased focus on the effects of climate change and halt any net increase in traditional hardening techniques and require the consideration of more sustainable alternatives (Connecticut Coastal Management Act, 2012). Research organizations, such as the Connecticut Sea Grant, have accordingly identified sustainable resiliency as key priority, with particular emphasis on reducing the effects of climate change (increased flooding and severe weather) on the at-risk communities along the state's shoreline (Connecticut Sea Grant, 2018).

This increased focus on the effects of climate change appears on the local management level as well. A 2013 NOAA survey found that 68% of Northeastern coastal resource managers' top priority was environmental conservation, followed by 61% indicating coastal planning and development (NOAA, 2014). Within these two priorities, managers also identified climate change impacts as the top sub-priority at 68% and 90%, respectively (NOAA, 2014).

One strategy with increasing emphasis as a primary mechanism for coastal adaptation to, and mitigation of climate change effects in Connecticut is the use of "green infrastructure". Green infrastructure is the "cost-effective, resilient approach to managing wet weather impacts" that "reduces and treats stormwater at its source while delivering environmental, social, and economic benefits" (U.S. Environmental Protection Agency, 2018). The most common coastal green infrastructure management approach is "living shorelines" which implement nature-based erosion control techniques that preserve natural features of the shoreline; as opposed to shoreline hardening structures (e.g. bulkheads, revetments, seawalls, etc.) that can increase erosion, inhibit ecosystem processes and eliminate natural habitat for native fish, animals and plants (NOAA, 2019).

As coastal communities increase their focus on mitigating the effects of climate change, they are not always able to incorporate town residents' preferences and values into their planning; particularly those residents who may not receive a direct benefit from the plan of which they contribute tax dollars towards. Coastal management plans intended to provide a public service that benefits the community, as a whole, may therefore distribute benefits unevenly on an individual level. Inclusion of public input periods during planning processes can capture some level of public preferences and help increase public support, but can vary widely based on the level of outreach and the framework for achieving effective public participation (Pohjola & Tuomisto, 2011). We therefore intend to use the results of this study to develop a quantitative model that can be used to evaluate the public's willingness to support (in the form of paying increased taxes) various coastal management plans and how specific outcomes of those plans affect support.

Specifically, we focus on citizens who do not own shoreline or near-coast property, but rather who live inland within a coastal community. By choosing to survey respondents that live outside the direct-defensive line of traditional armoring, we may be able to capture more heterogeneity in coastal planning preferences beyond the traditional emphasis on protection of shoreline structures (Schlacher, et al., 2007).

Given that almost 40% of respondents to the NOAA coastal resource manager survey indicated wanting to learn more about using economic methods to support decision-making, and nearly 93% indicated interest in building proficiency in engaging communities, we believe this study may serve as a resource that helps fill these needs for comprehensive, resilient coastal management (NOAA, 2014).

1.2 Literature Review

Attempts to value the environment have long been approached by pure environmentalists and researchers alike. These efforts have been increasing following the release of the Millennium Ecosystem Assessment (2005) which concluded that recent anthropogenic activities have changed ecosystems more than any other time in human history and that these changes are resulting in the reduced ability for ecosystems to provide resources that support human well-being (Millennium Ecosystem Assessment , 2005). Various approaches have included conservation biology which applies Pinchot-like intrinsic value to nature and strives to conserve as much biodiversity and ecosystem health as possible (U.S Forest Service, 2016), to natural resource management (i.e. ecosystem management) which seeks to balance humans' use of ecological resources with "all" the implications of that use; but even ecosystem management can have multiple interpretations and often pushes policy to focus only on ecosystem health (Swallow, 1996).

However, for most land-management decision makers (in this study's context, policy makers), decisions often come down to optimization of net present value. As defined by the World Bank, planning and zoning "allows local and national authorities to regulate and control land and property markets to ensure complementary uses," (The World Bank, 2018). Usually a parcel of land is reserved for the option that provides the highest net present value (Krutilla, 1967). Optimized economic welfare efficiently maximizes the discounted income stream that produces that net present value, measured by the quantifiable, productive output that the activity creates. Therefore, when a policy maker considers how to utilize a beach-front parcel of land, they evaluate the tradeoffs between using it as developable land or as conservation space for expansion of natural habitat and saltmarsh. However, the policy maker will quickly realize that these two land uses cannot be evaluated evenly because though most people will agree that the goods and services ecosystems provide ("ecosystem services") are valuable, existing valuation procedures struggle to integrate those values into decision-making (Krutilla, 1967; Swallow, 1996).

Krutilla (1967) summarized this conundrum, identifying three core reasons as to why natural resources, such as open coastal space, are difficult to value. First, the preserved, natural environment has no close substitutes, although the natural resource commodities that come from the environment can have alternative supplies. Secondly, the natural environment does not have "perfectly discriminating pricing," meaning that the net present value of land preserved as natural habitat cannot be measured based on market prices (Krutilla, 1967). Finally, the majority of natural resources are public goods. Pure public goods cannot be accurately valued without the inclusion of passive-use value and their value cannot be diminished for one person because another used it.

Creating policies for public goods based on research that does not include public preferences can affect their legitimacy and effectiveness (Evans, Noblet, Fox, Bell, & Kaminski, 2017). Thus, the role of the economist is to understand these preferences by identifying the contributions of ecosystem services to human welfare and how these contributions influence public support for conservation (Swallow, 1996).

Valuation research is often accomplished through stated preference (SP) methods which attempt to induce respondents to disclose their true preferences through a series of choice-based survey questions. SP methods continue to be a major approach to estimating values for changes in public goods (e.g. ecosystem services) today (Johnston, et al., 2017). Often referred to as the Choice Experiment (CE) method of stated preference research, respondents are asked to choose between different bundles of goods or services that are presented through attribute levels that vary between the choices, with one attribute usually being cost. This format allows researchers to understand how specific attributes influence an individual and their marginal willingness to pay (WTP) for a change to those attributes (Hanley, et al., 1998).

CE research has been used to understand public WTP for many different valuation scenarios but is ideal for research that tries to value individual, but concurrent, attributes and goods that are not traded in market transactions, such as ecosystem services. The context of Connecticut's coastline is a prime application for CE, where there are non-market attributes related to recreational activities such as fishing, shell fishing and hiking; values related to pure aesthetic appreciation or "coastal charm" appreciation; and values from saltmarshes like habitat provision, erosion control, and storm surge protection (Johnston, Magnusson, Mazzotta, & Opaluch, 2002). Washburn et al.'s (2018) review of the multiple applications of ecosystem services to coastal management found that the study of ecosystem services strongly supports interdisciplinary collaboration for measuring social and economic values that individuals apply to natural resources.

Our research builds upon existing CE studies applied to coastal ecosystem services in the Northeast. Survey-based research on the role of public preferences in optimizing coastal land preservation has focused on various attributes such as the magnitude of impacts on wetlands (Bauer, Cyr, & Swallow, 2004), the capacity for public access (McGonagle & Swallow, 2005), coastline erosion management (Kriesel, Landry, & Keeler, 2005), alternative funding resources for conservation efforts (McGonagle & Swallow, 2006), and water quality (Evans, Noblet, Fox, Bell, & Kaminski, 2017).

To our knowledge, no study to date has surveyed the entire Connecticut coastline using a CE survey design to understand coastal residents' attitudes towards impacts caused by storm surge and sea level rise adaptation and preferences for protecting or adapting built infrastructure and natural assets. Our survey design does build on a previous CE application used in the town of Old Saybrook Connecticut (Johnston & Abdulrahman, 2017) . Additionally, whereas similar research has surveyed a sample population of all coastal town residents our study targeted only residents that live more than 100 yards from a coastline.

1.3 Hypotheses

We hypothesize that inland coastal town residents will be willing to pay more for, or otherwise increase political support for coastal resilience action if (a) it does not adversely affect natural assets or ecosystem services; (b) it benefits distressed or lower-income households; (c) defensive benefits help to minimize damage to homes at-risk of repeated flood or storm damage; (d) coastal residents benefiting from the defensive adaptations bear a larger share of the cost; and (e) changes are made voluntarily by owners of at-risk built assets;.

Additionally, we will test whether the public's willingness to pay is conditional on their geographic location along the Connecticut coastline, and their latent attitudes that are in part affected by that location.

2 Methodology

2.1 Theoretical Model

The standard economic model for evaluating CE data is based on the random utility model (McFadden, 1974) and assumes a respondent, *n*, faces a set of choice situations, K, each with a set of alternatives for which utility (i.e. the satisfaction of that respondent) of choice option *i* is given by:

(1) $$U_{ni} = U(X_i,\ P_i, Z_n) = V(X_i,\ P_i, Z_n) + \varepsilon_i$$

where X_i is a vector of attributes associated with choice option *i* that influence utility directly, P_i is the cost of obtaining that option, and Z_n is a vector of socio-economic characteristics of *n*. The respondent's utility is also expressed as a deterministic component, $V(X_i,\ P_i, Z_n)$, and a stochastic component, ε_{ni}, modeled as the random error with a mean of zero.

Thus, a respondent will choose the *i*th option if and only if:

(2) $$U(X_i,\ P_i, Z_n) > U\left(X_j,\ P_j, Z_n\right),\ \ \forall i,\ \ \in\ K,\ and\ i \neq j$$

In other words, a respondent will choose option *i* given attributes, X_i, and cost, P_i, if option *i*'s utility exceeds the utility of all other options. In order to identify and quantify the effects of the vector of attributes on choice, we employ a random utility model expressed as:

(3) $$U(X_i,\ P_i, Z_n) = \ \beta_1 X_i + \beta_2 P_i + \alpha Z_n + \ \varepsilon_i$$

where $\beta_1$is a vector of parameters on utility-relevant attributes, β_2 is the parameter on cost, and α is a vector of parameters on socio-economic characteristics of *n*.

While a core purpose of stated preference research is to understand individual preferences, this study draws on data derived from the preferences of all coastal residents who will likely have a wide range of experiences and conditions that influence respondents' choices. This paper therefore attempts to go further and align with preceding findings that there are additional preference indicators within choice data that are unobservable to the researcher (Boxall & Adamowicz, 2002; Train & McFadden, 1987; Breffle, Morey, & Thacher, 2011; Hoyos, Mariel, & Hess, 2015; Kafle, Swallow, & Smith, 2015). The latent-class modeling (LCM) approach to interpreting preference heterogeneity develops a model using characteristics of respondents that seem to indicate that an individual has preferences that are better represented by one class of individuals than to any other groups. In our survey, we use respondents' answers to Likert scale questions to estimate a respondent's alignment with certain characteristics. The LCM approach groups respondents based on the assumption that there are underlying, latent preferences that help guide respondents' choices and can be used to match respondents with a latent class, *c*, where *c=1,2,…C* and can be characterized by a class-specific preference function (Kafle, Swallow, & Smith, 2015).

Following Kafle et al. (2015), we use an unconditional probability model that *n* is in class *c*, Π_{nc}, with the assumption that *n*'s class is unobserved, given as:

(4)
$$\prod\nolimits_{nc} = \frac{exp(\theta_c Z_n)}{\sum_{c'} exp(\theta_{c'} Z_n)}$$

where θ_c is a vector of parameters determining the probability that an individual has class membership, *c*; Z_n is a set of socio-demographic and attitude characteristics that apply to *n*, and c' is an index of summation across all classes (*c=1, 2…C)*.

Once we have *n*'s probability of membership in class *c*, we can estimate the conditional probability that they will choose coastal management plan *i* given as:

$$\prod_{nci}^{\sim} = \frac{exp[\mu_c(V_{nci})]}{\sum_{i'} exp[\mu_c(V_{nci'})]} \quad (5)$$

where μ_c is the scale parameter for *n* being in class *c* and is normalized to 1.0 for one of the classes, and V_{nci} is the set of specific utility parameters for class *c*.

The LCM approach is semi-parametric and assumes that individuals in the same class will have the same preferences, thus capturing preference heterogeneity by class membership (Kafle, Swallow, & Smith, 2015). This will allow us to refine the analysis of our standard multinomial logit model and control for unobservable differences respondents may have across the geographic scope of our survey. Figure 1, which is based on Boxall and Adamowicz' (2002) flow chart for applications in recreation in wilderness parks, outlines the application of the LCM to the Connecticut coastline where shaded boxes represent latent constructs used in the model.

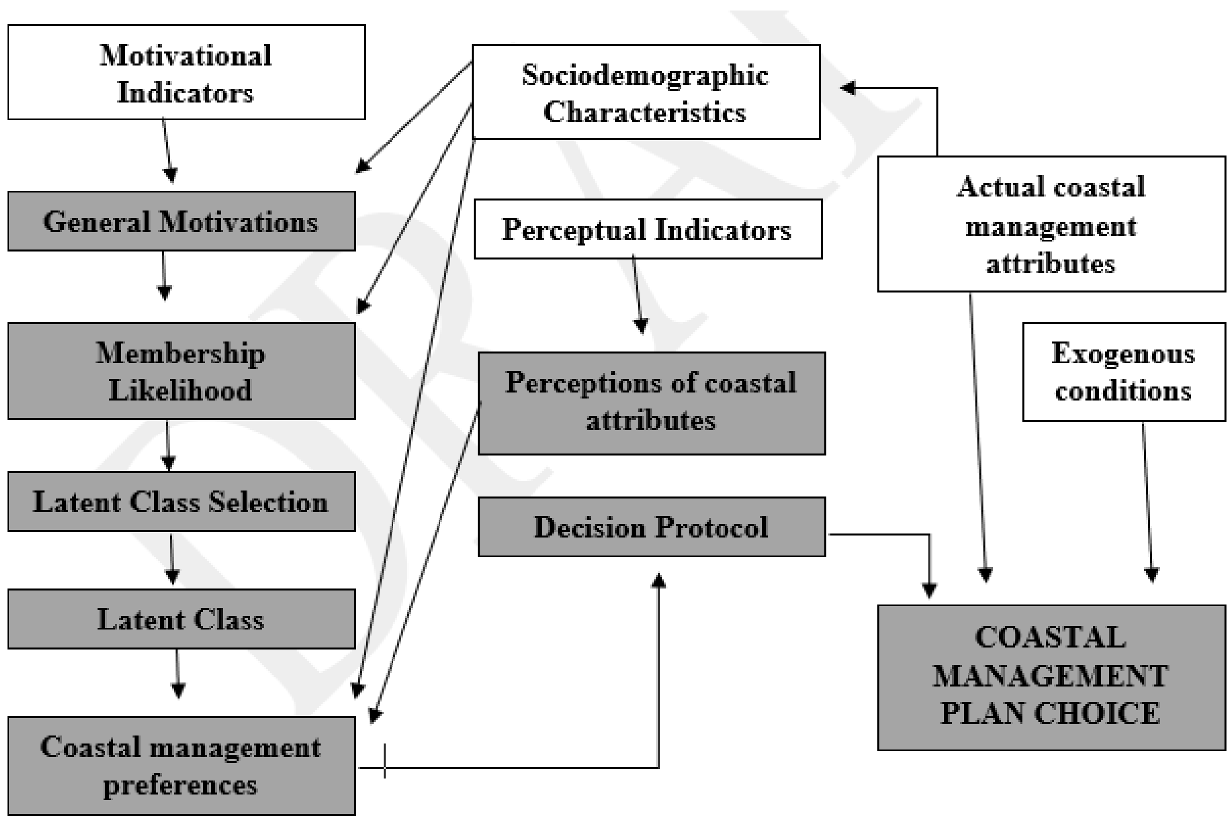


Figure 1: Path Diagram for the Application of LCM of Coastal Management Choices

2.2 Experimental Design

2.2.1 Development process

Stated preference research is desirable for studying economic values of goods that do not have formal, existing markets, particularly environmental goods. Traditional market goods typically require direct interaction for them to provide economic utility or value to the consumer. However, unlike most traditional goods, ecosystem services provide value that benefit many people simultaneously and can have passive-use value, also known as existence, intrinsic, inherent, stewardship, or non-use value (Carson R. T., 2000).

Stated preference studies allow for such environmental attributes to be itemized and valued by creating a theoretical market. However, it is the use of hypothetical markets has raised concern over whether stated preference data is reliable or valid enough to be considered equivalent to revealed preference data, and if it conforms to economic maxims (Carson R. T., 2000). Carson (2000) has argued that the primary cause of this concern is less about the practice of stated preference itself, and more about the quality of individual studies. Therefore, preparing a high-quality stated preference-based study requires careful consideration of multiple design choices.

The NOAA Blue Ribbon Panel's report has served as a primary set of guidelines for preparing high quality SP studies since 1993 (Arrow, et al., 1993). However, twenty-five years of both academic and government-lead research has occurred since then, necessitating a contemporary set of guidelines. In 2017, a group of twelve economists with substantial experience with SP studies released an updated, comprehensive set of guidelines grounded in the growing body of peer-reviewed literature (Johnston, et al., 2017). These guidelines contain specific recommendations which we have attempted to consider in preparing this study.

2.2.2 Choice Experiment Survey

The primary goal of SP valuation research is to produce estimates of value that can be considered valid and accurate estimates of true value by minimizing bias. A study's success at achieving this goal depends on how respondents perceive the good being valued; either as a "package" or as an individual characteristic of a good (Johnston, et al., 2017). Respondents' perception affects whether the researcher uses contingent valuation (CVM), or a CE approach to SP valuation. Contingent valuation method questions estimate the value of a fixed set of changes by asking respondents to state their maximum WTP to obtain, or minimum compensation amount required to forego a hypothetical scenario that increases (or decreases) some environmental quality (Hanley, et al., 1998). Alternatively, CE formats estimate the value of individual attributes by asking respondents to choose between different bundles of those attributes, each with varying provision levels (Hanley, et al., 1998). When a respondent is given multiple sets of choice scenarios at changing attribute levels, researchers can infer which attributes significantly guide the respondent's decision (Hanley, et al., 1998).

In this study, we employ the CE approach to SP valuation, however, there is risk in utilizing CE techniques, especially in its effect on scenario complexity. Complex choices with multiple attributes have been shown to prompt respondents to use simplifying heuristics inconsistent with utility maximizing decision strategies (Boxall, Adamowicz, & Moon, 2009; Cameron, DeShazo, & Johnson, 2009). Our study uses varying proposed management plans to address sea level rise and coastal flooding and shows possible outcomes of those plans on the local coastal environment and infrastructure. Given the uncertainty of the true outcomes of proposed SLR action plans due to uncontrollable, external factors (e.g. the rate of future global carbon emissions and their impact on climate) the CE format allows us to consider what specific attributes or conditions increase WTP (i.e. public support). , while holding all other attributes constant. Existing research has shown that qualitative pre-testing of choice experiments in the design phase can help researchers minimize confusion and complexity of a CE for respondents, as can proper parameterization during the modeling phase (DeShazo & Fermo, 2002). We summarize our efforts in the following sections.

2.2.3 Qualitative Pre-testing; Focus groups

To prepare a CE survey that is consequential, and understandable, the perceptions of survey respondents must be carefully taken into consideration. In order to capture these perceptions and ensure that respondents understand survey questions as intended by the researchers, we conducted initial pretesting in the form of six focus groups, held between February and December of 2017. Recruitment for each focus group was publicly advertised through outreach to local environmental and volunteer societies, churches, libraries, parent-teacher organizations, and social media ads. The first five focus groups were held in five communities along the Connecticut coastline (Old Saybrook, Clinton, Madison, Milford, and Mystic). Each group lasted two hours long, primarily in the evening to accommodate work schedules, and contained four to eight participants. Participants were compensated fifty dollars for completing the session and provided signatures confirming that they had been paid.

The final focus group was a more informal structure held at a library in Mystic at which we had previously hosted a two-hour session with participants recruited through the recruiting initiatives described above. In this session, we offered library patrons twenty-five dollars to take our survey and spend ten to fifteen minutes afterwards providing feedback and discussion. These abbreviated sessions also allowed us a higher volume of participant feedback given the shorter time frame. As this was the final focus group, we felt that we had mostly captured local perceptions in the first five sessions, and needed more direct, one-on-one discussion of the survey content. Additionally, as participation in the session took only about half the time, we pro-rated the compensation.

During all the sessions we employed ethnographic interviewing techniques in order to prevent discussion that led to unintended biased support from the groups. Ethnographic questions lead respondents to share the perceptions, past experiences, and knowledge that guide their behavior which helps to assure researchers that respondents have a clear understanding of the meaning of the questions and responses (Johnston, Weaver, Smith, & Swallow, 1995). Examples of feedback that led to modification included the removal of confusing diagrams in early versions of the survey and the clarification of coastal terminologies and choice questions through the inclusion of a short instructional video in the survey (The script to the video can be found in Appendix D).

2.2.4 Establishing the Status Quo

One of the core issues revolving around research on the effects of sea level rise is that there is a great deal of uncertainty about its effects, especially as projections attempt to predict the future. Whereas the baseline scenario in many choice experiment surveys present current-day conditions of the environment when no action is taken, the climate change context motivated us to present the possible future baseline conditions produced by no action. This posed considerable challenges as we essentially were asking respondents to compare the utility of hypothetical scenario choices, to a baseline of projected outcomes under a no-action status quo, rather than a baseline of current-day environmental conditions.

2.2.4.1 Selection of the Sea Level Rise Model

As a result, it was critical that we carefully consider how respondents would perceive the risk and uncertainty involved in our chosen baselines and that we establish a credible baseline. First, we recognized that the geology and settlement of Connecticut's shoreline is varied and would likely have different baselines for a status quo. We referred to the New England Interstate Water Pollution Control Commission's (NEIWPCC) 2015 report on the Application of Sea-level Affecting Marshes Model (SLAMM) to Coastal Connecticut in order to better understand the potential inundation levels and land loss different regions can expect due to sea level rise (SLR) through 2100. This report was particularly useful due to its locality and granularity of model outputs, multiple layers of geographic elevation data, its inclusion of multiple SLR scenarios, and its ability to account for second order effects of SLR such as wave action, its erosion effects, and marsh accretions.[2]

The true impacts of SLR are uncertain as they are contingent on multiple variables including population, economic activity, technological innovation, governance, fuel consumption and type, and lifestyles all over the world (Intergovernmental Panel on Climate Change, 2018; New England Interstate Water Pollution Control Commission, 2015). The NEIWPCC (2015) report used a range of possible SLR scenarios including the General Climate Model, the minimum and maximum of the Rapid Ice Melt model, and the intermediate scenario of 1 meter by 2100. We selected the 1m by 2100 model because it scored the highest in the probability density function and is supported by subsequent, similar research findings on projected SLR in Connecticut (O'Donnell, 2018).

[2] Marsh accretion is defined as "the process of wetland elevations changing due to the accumulation of organic and inorganic matter. Accretion is one of the most important processes affecting marsh capability to respond to SLR," (New England Interstate Water Pollution Control Commission, 2015).

2.2.4.2 Time-step for Projections

Next, since we are attempting to understand how ecosystem services affect public support for various SLR adaptation measures, our no-action status quo baseline needs to reflect that the magnitude of incremental SLR impacts is usually easier to visualize on a longer-term basis rather than day-to-day. Identifying the meaning of “long-term" required selecting a SLR scenario and timeframe that is both credible and relevant to respondents, and long enough to demonstrate perceivable impacts.

While many climate projections look to the 2050 or 2100 timesteps, the NEIWPCC report (2015) models use a base year of 2002 and use time steps of 2025, 2055, 2085, and 2100. We selected 2055 because it would be likely that many of our respondents would either still be alive at that point or have immediate family members alive. Additionally, related research and applications also commonly use 30-year timeframes for risk-related planning, such as home mortgages, and 2055 is closest to that (O'Donnell, 2018). This timestep was also supported by our focus groups during which participants discussed that they did not see climate change as a problem in the next five or ten years but could in 20 or more.

2.2.4.3 Establishment of the Four Regions

Though there are 36 towns in Connecticut that are considered “coastal”, only 24 of them border the Long Island Sound (LIS). We opted to consider only the 24 coastal towns bordering the LIS as they are most likely to experience coastal flooding from SLR and storm surges.[3] These 24 towns each fell into one of six watersheds identified by the NEIWPCC (2015) report.

[3] Many of the other towns that are considered coastal fall along the Thames River, Housatonic River, and Connecticut River. Storm surges can cause rivers to rise and flood nearby land. While this is a result of sea level rise and storm surges, we did not consider this “coastal flooding” in the context of this study.

In Connecticut, councils of governments (COGs) serve as the regional planning organizations (RPOs) for their member towns and communities, providing land use and zoning regulations or ordinances guidance, as well as preparing multi-jurisdictional hazard mitigation plans for these member communities (CT DEEP, 2014). Based on this existing management structure and feedback from focus groups which confirmed that respondents expect regional approaches to coastal management, our choice questions provided coastal management plan options on the regional level rather than town-by-town. To set these regions, we compared COG territories that included towns on the LIS shoreline with the SLAMM project sites and watersheds (New England Interstate Water Pollution Control Commission, 2015), resulting in four regions of six towns, displayed in Table 1.

The SLAMM maps allowed us to identify which watershed each town fell into, and to then apply the initial land cover type proportions for each watershed to the square acreage of each town. We then used the initial land cover estimates from NEIWPCC (2015) to develop a baseline of existing salt marsh and beaches in each region. We aggregated the land cover-proportionate estimates to estimate each regional baseline.

Table 1: Summary of Survey Regions

Region	Coastal Position	Towns
Region A	West	Greenwich, Stamford, Darien, Norwalk, Westport, Fairfield
Region B	West-Central	Bridgeport, Stratford, Milford, West Haven, New Haven, East Haven
Region C	East- Central	Branford, Guilford, Madison, Clinton, Westbrook, Old Saybrook
Region D	East	Old Lyme, East Lyme, Waterford, New London, Groton, Stonington

2.2.4.4 Households At-risk

Our status quo included five attributes that required scientific support to be considered realistic predicted outcomes with no action: homes at risk of repeated flood damage, acres of salt marsh impacted, miles of beach impacted, fish and shellfish population impacted, and major local roads impacted. The acres of salt marsh and miles of beach impacted were projected using the 1m by 2100 model from the NEIWPCC report (2015). However, we also needed to provide a realistic estimate of the number of households that will be repeatedly impacted by flooding if no action is taken.

NOAA uses the hydrodynamic model known as the Sea, Lake, and Overland Surges from Hurricanes (SLOSH) to predict storm surges along the East and Gulf Coast. Zachary et al. (2015), paired this model with elevation data to create refined maps that display expected storm surge inundation for various storm categories, creating estimates for population at risk for each state for each hurricane category. In Connecticut, 57.9 thousand households, or roughly 12.5 percent of total coastal households are anticipated to be inundated in the occurrence of a Category 1 hurricane (74-95 mph sustained wind) (Zachry, Booth, Rhome, & Sharon, 2015).

Using this estimated proportion, we calculated the number of households in each region using Census Bureau data and applied the 12.5 percent to achieve an estimate of households at risk by region. This estimate does not consider population change or increased development through 2055, but rather asks respondents to consider the fact that this many households, at a minimum, will have a very high probability of being inundated by a Category 1 hurricane by 2055. By selecting Category 1, we indicate that these households will be repeatedly damaged by coastal flooding from extreme weather events through 2055, though this is a conservative number in the event of stronger weather.

2.2.4.5 Nuisance Flooding Days

We also incorporated research regarding nuisance flooding in Connecticut into our no action baseline attributes. Nuisance flooding is also referred to as “high tide flooding” and is defined as “flooding that leads to public inconveniences such as road closures,” and “is increasingly common as coastal sea levels rise,” (National Ocean Service, 2018). NOAA has reported on how SLR affects nuisance flooding around the country, with estimation sites for Connecticut located in New London and Bridgeport (National Oceanic and Atmospheric Administration, 2014). Both cities have reported upward trends of both mean sea level (MSL) and number of days with nuisance flooding per year since 2000. For example, Bridgeport increased its number of nuisance flooding days from approximately five days per year in 2000, to almost 25 days per year in 2012. New London showed similar trends though at a smaller scale, increasing from about one day a year, to five by 2012. Though the average between these two cities was 15 days per year, the average annual percent change over that timeframe was approximately 22 percent. Given the positive expected growth rate of nuisance flooding days at measurement sites and the predicted growth of SLR, we opted to select 25 days per year as our statewide baseline if no new action is taken. This decisions results in a potentially conservative estimate, but without access to data for all the coastal towns, each varying in elevation and infrastructure design, we opted to implement one baseline across all four regions.

2.2.4.6 Effects on Fish and Shellfish Populations

Finally, we included fish and shellfish population as an attribute that would represent the impact the effects of no new action on local wildlife. The Long Island Sound Study’s (LISS) Habitat Restoration Initiative identifies 12 coastal habitats critical to supporting healthy wildlife populations such as tidal wetlands, eelgrass, shellfish reefs, and riverine migratory corridors (LISS, 2018). These habitats have been destroyed or degraded by human development over the years and based on the NEIWPCC (2015) SLAMM models, are at risk to be inundated and further damaged by SLR and storm surges throughout the 21st century. This limits fish migration and spawning, as well as sheltered habitat for shellfish. Though the LISS does collect annual surveys to estimate fish populations native to the LIS, it does not report on the various effects of development or SLR. We selected a proxy baseline of a 15% decline in local fish and shellfish populations by 2055 to indicate habitat degradation from various activities both at the local and global levels.

2.2.4.7 No-Action Status Quo Attribute Estimates by Region

Considering both local and national studies allowed us to develop unique no-action status quo baselines for each of the four regions, allowing us to acknowledge the variance of Connecticut's coastline, in order to increase the credibility of scenarios to respondents. The final estimates of the baseline are indicated in Table 2.

Table 2: Baseline Attribute Levels by Region

	Homes at Risk for Repeated Flood Damage[a]	Salt Marsh at Risk[b]	Beach at Risk[b]	Impacts of Local Fish/Shellfish [c]	Estimated Nuisance Flooding Days[d]
Region A	20,000	72 acres	1 mile	15% loss	25
Region B	24,000	530 acres	3.5 miles	15% loss	25
Region C	6,700	1,335 acres	6.9 miles	15% loss	25
Region D	5,000	133 acres	0.7 miles	15% loss	25

[a] Values determined by author with based on information provided by Zachry, Booth, Rhome, & Sharon (2015), and U.S. Census Bureau data
[b] Values determined by author with based on information provided by New England Interstate Water Pollution Control Commission (2015)
[c] Values determined by author with based on information provided by Long Island Sound Study (2018) and the National Ocean Service (2018)
[f] Values determined by author with based on information provided by National Oceanic and Atmospheric Administration (2014)

2.2.5 Plan Choice Questions

Our survey included three types of choice questions, each asking respondents to consider three alternative coastal management plans. Each alternative coastal management plan listed the possible outcomes related to SLR across the six towns in the respondent's region. Alternatives contained nine attributes; Homes Bought Out, Homes Protected, Saltmarsh Acres Lost, Beach

Miles Lost, Rate of Voluntary Offer Acceptance, Fish/Shellfish Population Lost, Days of Nuisance Flooding, At-risk Homeowners' Share of Plan Cost, and Property Tax Payment by the respondent (see Table 2 for specific attribute levels by region). These attributes were used to create three types of CE questions.

"Type 1" questions included all the attributes which each would vary by plan option within a question. This format allowed for participants to indicate their preferences between all a possible plans' attributes as compared to the status quo. Each "Type 1" question included a status quo plan called "No New Action" (i.e. no action has been or will be taken to adapt to SLR), and two alternative plans called "Proposed Plan A" and "Proposed Plan B". In "Type 1" questions, respondents consider plans that would produce results different than the "No New Action" status quo.

"Type 2" and "Type 3" questions introduced hypothetical scenarios where the local policy-makers (i.e. local government) of respondents' towns would have already designed a plan that would achieve some outcomes different than those of the original baseline status quo. Respondents were informed that this plan would come at no new cost to them because it would be funded using a combination of grants, and reallocation of existing tax revenues. Respondents were asked to choose between this "Current Plan" that would serve as the status quo, and modifying the plans by selecting either "Alternative Plan A" or "Alternative Plan B". In each question, one of the alternative plans would modify the "Current Plan" to have a changed impact for a subset of attributes and would come at a tax increase to respondents, whereas the other alternative plan would modify the "Current Plan" to lower its impact for a subset of attributes back to their original no-action status quo levels represented by the “No New Action” plan presented in the “Type 1” questions, and would provide a tax reduction to respondents.[4]

The key difference between the “Type 2” and “Type 3” questions was that “Type 2” questions presented situations where the policy makers’ no-cost “Current Plans” were designed to impact only built infrastructure (e.g. houses and roads), and the “Type 3” questions no-cost “Current Plans” were designed to impact only natural resources (e.g. beaches, salt marsh). In “Type 2” questions, the alternative plans would hold the built infrastructure attribute levels constant across all three plan options and allowed the natural resource attributes to vary. This allowed us to focus more closely on participant preferences for ecosystem services, without the need to weigh the complex tradeoffs against built infrastructure protection. Similarly, “Type 3” questions held natural resource attributes constant across all three plans but allowed built infrastructure attributes to vary. Example choice questions for each type can be found in Appendix A.

We used NGene software to generate independent efficient experimental designs for each of these sets and attributes using D-efficiency criterion to minimize the variance-covariance matrix for main effects (Kuhfield, 2005).

In “Type 1” questions where every attribute could vary, NGene produced 36 choice questions, while for “Type 2” and “Type 3”, it produced 24 choice questions. Ngene efficiently blocked 12 groups of three “Type 1” questions, 12 pairs of “Type 2” questions, and 12 pairs of “Type 3” questions, leading to 12 versions of the survey which each included three “Type 1” questions,

[4] The creation of “Type 2” and “Type 3” questions originated from focus group participants asking why coastal management outcomes could not be accomplished using existing tax revenue. We believe that this concern arose in focus groups more consistently than it may have in other studies’ focus groups because Connecticut has been experiencing a climate of political controversy surrounding multiple state budget crises, and cycles of tax increases in a state that many people have perceived as already being highly taxed. The logic of “Type 2” and “Type 3” questions’ design was that by lowering the impact of a plan that already does not require any new funding, policy-makers would adjust the funding necessary for the plan and could return the cost reductions back to taxpayers.

and two each of “Type 2” and “Type 3”, for a total of seven choice questions. Because we independently generated the efficient experimental designs for each question type, we were able to arrange them in different orders within each version to mitigate ordering effects. Each survey version thus had two orders, with evenly-numbered survey versions (i.e. 2,4,6,8,10,12) taking the orders “Type 2- Type 3- Type 1” or “Type 1- Type 2- Type 3”, and oddly-numbered survey versions (i.e. 1,3,5,7,9,11) taking the orders “Type 3- Type 2- Type 1” or “Type 1- Type 3- Type 2”.   With 12 survey versions each with two orders, we produced a total of 24 possible surveys a respondent could receive.

As previously described, we divided the Connecticut shoreline into four regions, each comprised of six coastal towns.   Each region received the set of 24 efficiently grouped survey versions, with attribute levels adjusted to reflect that region’s land composition and conditions. Thus, our study evaluates data gathered from a total of 96 forms of the survey.

2.2.5.1 Description of attributes

The final set of attributes was adjusted proportionally to each region’s no-action status quo. Some proportions were pre-determined such as the proportions of “At-risk Homes Bought Out” and “At-risk Homes Protected” at levels of 5%, 15%, and 25%, and 70%, 55%, and 35% respectively. For attributes such as “Saltmarsh Lost” and “Beaches Lost”, proportions were calculated by taking the no-action levels of loss and dividing them by the total acres of saltmarsh, or miles of beach in order to adjust for differing levels by region. The “High” level was then set to be equivalent to 90% of a region’s no-action level, “Medium” was 50% of the no-action level, and “Low” was 10% of the no-action level. If an attribute’s baseline did not differ region to region in the survey, the levels remained constant across the regions (e.g. “Fish” in

Table 3). Table 3 summarizes these attributes and levels. Appendix A demonstrates the presentation of the attributes.

Table 3: Attribute Levels by Region

	No-Action Status Quo	High	Medium	Low
Region A: Greenwich, Stamford, Darien, Norwalk, Westport, Fairfield				
At-risk Homes Bought-Out %	0%	25%	15%	5%
At-risk Homes Bought-Out Quantity	-	5,000	3,000	1,000
At-risk Homes Protected %	0%	70%	55%	35%
At-risk Homes Protected Quantity	0	14,000	11,000	7,000
Saltmarsh Lost %	11%	10%	5%	1%
Saltmarsh Lost Quantity (Acres)	72	66	33	7
Beaches Lost %	4%	3%	2%	1%
Beaches Lost (Miles)	1.00	0.70	0.50	0.20
Region B: Bridgeport, Stratford, Milford, West Haven, New Haven, East Haven				
At-risk Homes Bought-Out %	0%	25%	15%	5%
At-risk Homes Bought-Out Quantity	-	6,000	3,600	1,200
At-risk Homes Protected %	0%	70%	55%	35%
At-risk Homes Protected Quantity	-	16,800	13,200	8,400
Saltmarsh Lost %	16%	15%	8%	2%
Saltmarsh Lost Quantity (Acres)	530	492	268	66
Beaches Lost %	14%	13%	7%	1%
Beaches Lost (Miles)	3.50	3.30	1.80	0.30
Region C: Branford, Guilford, Madison, Clinton, Westbrook, Old Saybrook				
At-risk Homes Bought-Out %	0%	25%	15%	5%
At-risk Homes Bought-Out Quantity	-	1,675	1,005	335
At-risk Homes Protected %	0%	70%	55%	35%
At-risk Homes Protected Quantity	-	4,690	3,685	2,345
Saltmarsh Lost %	17%	16%	6%	2%
Saltmarsh Lost Quantity (Acres)	1,335	1,232	693	154
Beaches Lost %	29%	26%	14%	3%
Beaches Lost (Miles)	6.90	6.20	3.40	0.70
Region D: Old Lyme, East Lyme, Waterford, New London, Groton, Stonington				
At-risk Homes Bought-Out %	0%	25%	15%	5%
At-risk Homes Bought-Out Quantity	-	1,250	750	250
At-risk Homes Protected%	0%	70%	55%	35%
At-risk Homes Bought-Out Quantity	-	3,500	2,750	1,750
Saltmarsh Lost %	9%	8%	5%	1%
Saltmarsh Lost Quantity (Acres)	133	115	72	14
Beaches Lost %	10%	9%	5%	1%
Beaches Lost (Miles)	0.70	0.60	0.40	0.10
All Regions				
Rate of Voluntary Offer Acceptance	0%	80%	60%	40%
Fish/Shellfish Population Lost %	15%	10%	5%	0%

Days of Nuisance Flooding	25	22	15	7			
At-risk Homes Share of Plan Cost	0%	60%	40%	20%			
All Regions Property Tax Payment	Status Quo	Context[a]	High	→			Low
Type 1 Questions	$0	($200)	$1,200	$900	$750	$500	$200
Type 2 Questions	$0	-	$1,200	$900	$750	$500	$200
or tax reduction	($200)	-	($1,200)	($900)	($750)	($500)	($200)
Type 3 Questions	$0	-	$1,200	$900	$750	$500	$200
or tax reduction	($200)	-	($1,200)	($900)	($750)	($500)	($200)

[a]The "Context Variable" serves to create formatting consistency across choice question Types. This ensures that respondents are exposed to the possibility of receiving a "Tax Reduction" in all choice questions, regardless of the order of the question types in the physical survey. In the case that a Context variable is used in a question, it applies across the options. In other words, if status quo states that the respondent would receive a tax reduction of $200, we deduct $200 from the cost of the other two plans.

2.2.6 Incentive Compatibility

The validity of a stated preference CE relies primarily on whether respondents make choices as they would under incentive compatible conditions. In other words, does the survey elicit the most optimal, utility-maximizing choice from respondents? There is substantial disagreement as to whether this is possible for stated preference research, given its usually hypothetical format. Generally, the single, binary-choice question is the preferred format for incentive compatibility in public good valuation, with other formats violating incentive compatibility (Carson & Groves, 2007). As our survey uses multiple trichotomous choice questions, it is inherently in violation of incentive compatibility. Regardless, there is a growing base of agreed-upon properties that encourage respondents to truthfully state their preferences, many of which we have implemented as an application of best practices in SP survey design (Whitehead, Blomquist, Ready, & Huang, 1998; DeShazo & Fermo, 2002; Carson & Groves, 2007; Taylor, Morrison, & Boyle, 2010; Vossler, Doyon, & Rondeau, 2012; Vossler & Watson, 2013; Johnston, et al., 2017).

2.2.6.1 Measuring Consequentiality

Carson and Groves (2007) correctly argued that a necessary condition for incentive compatibility of a SP survey is whether the respondent views their choice as "consequential" which has been supported by other empirical findings (Herriges, Kling, Liu, & Tobias, 2010; Vossler, Doyon, & Rondeau, 2012). Consequentiality is typically the result of two assumptions; one, being that the respondents care about the impacts of at least some policies being proposed in a survey, and the other that the respondent believes their response to be influential in the final outcome (Vossler, Doyon, & Rondeau, 2012).

Though our survey is not incentive compatible, our multi-attribute CE makes it more difficult for respondents to strategize and choose an option that fails to identify their best option within the question. We therefore rely on cognitive dissonance and assume that respondents choose their first-best option within the CE question, each time. Additionally, in order to capture beliefs and levels of concern about the topics covered by this study, our survey included a series of Likert-Scale questions about their levels of concern on various impacts of sea level rise and coastal flooding.

Following the completion of the choice questions, respondents were asked to rate their belief that the outcomes of this survey would be used by policy-makers. These questions can allow us to measure the survey's effectiveness of meeting the assumptions for consequentiality.

2.2.6.2 Payment Vehicle

The selection of payment vehicle type used in a stated preference survey has been shown by several studies to be influential on welfare estimates (Johnston, Swallow, & Weaver, 1999; Morrison, Blamey, & Bennett, 2000). Typically, an incentive compatibility payment vehicle must, at a minimum, be nonvoluntary to prevent or discourage free riding. However, beyond that, there is no consensus on which specific vehicle is best (Johnston, et al., 2017). In past economic studies concerning coastal management projects, researchers have employed user fee-financing as the payment mechanism (Kriesel, Landry, & Keeler, 2005). The reasoning behind this decision is that the fee is paid by the direct beneficiaries of an improved resource, making it politically agreeable.

However, as we focused on measuring the public support for coastal management plans from those whose homes likely would not benefit from the direct protection, we chose to use a more traditional and universal payment vehicle in the form of a property tax payment. This payment vehicle is coercive and therfore encourages respondents to accept the policy relevance, consequentiality, and plausibility because it is a realistic payment mechanism (Mitchell & Carson, 1989).

2.2.6.3 Trichotomous Choice Questions

Human choice literature suggests that an increase in choice set complexity will decrease choice consistency, which also supports the preferred single, binary-choice question for incentive compatible stated-preference research (DeShazo & Fermo, 2002; Carson & Groves, 2007). However, binary choices for real public goods are not always feasible given the multiple available alternatives, and in the applications of CE there is not a clear consensus on whether binary or multinomial choice formats are preferred (Johnston, et al., 2017).

Addressing SLR and coastal flooding is inherently complex and has a wide range of possible actions and both intended and unintended impacts. Therefore, despite tradeoffs with complexity, this survey implemented a trichotomous choice format in order to capture respondents' consideration of these options. The trichotomous format is also consistent with formats used in recent, related research on Connecticut's shoreline (Johnston, Makriyannis, & Whelchel, 2018). It should be noted that in recognition of the increased complexity, we prepared a short video for respondents to watch just before answering their choice questions that was designed and tested in focus groups.[5] The video provided background information on the terminology and implications of different measures, as well as further explanation of the choice questions' scenarios. Focus-group participants reported the video to be effective at providing clear instructions for approaching the choice questions, as well as background information.

2.2.7 Willingness to Pay and Willingness to Accept

At the core of Hicksian welfare theory are compensating surplus (CS), and equivalent surplus (ES), which are, respectively, interpreted as WTP to obtain and willingness-to-accept (WTA) to forego a desired change. Standard practice in stated preference research is to choose one as the welfare measurement depending on whether the public good being studied is considered an improvement or a degradation, and whether the change affects an individual's property rights (Kim, Kling, & Zhao, 2015). This is normally shown through an individual's indirect utility function, $v(p,q,m)$, where p is the price for a bundle of goods, q is the environmental quality, and m is their income. In a scenario where q_0 is the current environmental status quo, and q_1 is the proposed new quality level, $q_1>q_0$ indicates an improvement and the reverse inequality indicates degradation. In the scenario of environmental improvement that an individual wishes to obtain, their indirect utility can be used to identify their compensating surplus

$$v(p, q_0, m) = v(p, q_1, m - CS(m)) \tag{6}$$

In this situation, $CS(m)$ represents the decrease in income (i.e. a maximum payment) that the individual would be willing to pay in order to achieve the improvement, recognizing that the maximum voluntary payment just allows the individual to maintain their initial utility with q_1 rather than q_0. This theoretical foundation supports many previous SP studies related to

[5] See the weblink included in Appendix D.

environmental conservation and ecosystems services (McGonagle & Swallow, 2005; Johnston, Makriyannis, & Whelchel, 2018). However, as previously discussed, in the "Type 2" and "Type 3" questions in our survey respondents are asked to choose between an improvement plan, a plan with some degradation and some improvement, and a plan that provides more improvement. Since one alternative in each of the "Type 2" and "Type 3" questions could present tax reductions, our survey is established to allow estimates of ES or CS (see Table 3).

2.2.8 Respondent Attitude questions

Stated preference questions can help policy makers measure the social value of the coastline and its attributes in economic terms, but responses to these questions do not always capture broader beliefs held by respondents. Incorporating attitudinal assessment questions into survey design can help to account for the noneconomic values people have that contribute to their willingness to pay for coastal adaptation plans (Purdy & Decker, 1989). In our survey, we used a modified version of McGonagle and Swallow's (2005) Coastal Attitude and Values Scale (CAVS), which were adapted from Purdy and Decker's (1989) attitude scales for wildlife. Our Modified Coastal Attitude and Values Scale (MCAVS) retained eleven of the original seventeen statements used in CAVS and include three new statements for a total of fourteen. The statements that were dropped were not used because they were integrated or captured in another statements or were not relevant to our study.[6] The new statements we included were designed to expand our understanding of people's attitudes regarding the differences between private and public coastal lands and how they could be impacted by different plans.

[6] CAVS was developed for McGonagle and Swallow's (2005) study of open space and public access whereas our study focuses on adaptation plans in the face of sea level rise.

Responses to these statements enter a principal component analysis that converts them to continuous “standardized scores” that measure various components of a respondent’s attitudes (Purdy & Decker, 1989).

2.2.9 Survey Sample Population Selection

We obtained the Connecticut Voter Registration list from the Secretary of the State in November 2017. Using the addresses in the list, we narrowed our pool to voters within the 24 coastal towns that border the LIS (Table 1). To further focus our survey, we mapped this pool of voters’ addresses and buffered out any addresses within 100 yards from the coastline (including estuaries and river mouths). From this population, we randomly selected 12,000 addresses split evenly across the four regions (3,000 per region), and within each regions’ six towns (500 per town). The 24 survey versions (12 versions, two orders), do not evenly divide into 500, meaning each town received approximately 21 of each survey version. Because we are attempting to survey a sample of the entire coastline population with the availability of analysis at a sub-group level, we did not adjust for town population.

2.2.10 Survey Implementation

The primary mechanism for implementing our survey was through the online survey platform, Qualtrics. This allowed us to upload each regions’ 24 versions with two orders, track the survey responses through individual web links, and to reduce the printing and mailing costs associated with multiple paper-mail surveys. Inspired by the Total Design Method, requests for participation in the online survey were sent five times over the course of June to September, 2018 to a sample population of 12,000 (Smyth, Dillman, Christian, & O'Neill, 2010). The mailings alternated between business letters on UConn letterhead, and postcards with more succinct content (see examples in Appendix E).

We achieved a response rate of 9.5% (1,147 responses) resulting from the letters and postcard reminders, though only 952 of the respondents provided responses to at least one of the choice questions, equating to an 8% usable response rate (Table 4). This is likely due to a series of obstacles that we believe inhibited or deterred respondents. The first issue was our initial "link-shortener", a web-based tool that consolidates a long weblink with many numbers, letters, and symbols, into a shorter link with about a dozen characters. In previous studies that used a similar method, respondents could not distinguish the letter "el" from the number "1", the capital letter "Oh" from the number "0", and so on. We provided a key on the business letter to help respondents identify letters and numbers, but this did not appear to be as useful as we intended. In the subsequent mailing we upgraded to a new "link-shortener" that allowed us to customize our shortened links. Not only did this upgraded shortener help us to create simpler, more approachable links for respondents, but allowed us to create links that simplified the identification of which survey was taken by a respondent.

Table 4: Survey Responses by Region

	% of Sample	Number
Region A: Greenwich, Stamford, Darien, Norwalk, Westport, Fairfield	19%	177
Region B: Bridgeport, Stratford, Milford, West Haven, New Haven, East Haven	17%	159
Region C: Branford, Guilford, Madison, Clinton, Westbrook, Old Saybrook	34%	327
Region D: Old Lyme, East Lyme, Waterford, New London, Groton, Stonington	30%	288
Total	100%	952

The second obstacle was coordinating the mailing times. Though we planned for one-week intervals between mailings, challenges with the selected printing vendor created significant delays. Additionally, given the wide geographical scope that the study covered, it was challenging to coordinate equivalent delivery dates. We did not test for the effect of the sequence of mailings and their timing, but it is reasonable to assume that this may have impacted our mailing.

Lastly, it has been reported that 48% of the average household's mail is junk mail, and 44% of that is immediately thrown away (Nixon, 2012; Wambuguh, 2011). Thus, it is conceivable that a recipient of our invitations to participate may have considered them junk mail and immediately discarded the invites. Despite our efforts to prevent discarded surveys thorugh the careful use of authentic logos, signatures, and professional formatting, it is impossible to rule this out as a cause of low response rates.

3 Results

3.1 Descriptive Statistics

Respondents were asked a series of socioeconomic and demographic questions at the end of the survey. Appendix H.1 summarizes the mean and mode of this sample. Table 5 further summarizes by region and compares these findings to actual regional demographic statistics taken from the Connecticut Department of Economics and Community Development's Economic Resource Center (DECD) (Connecticut Economic Resource Center, 2018). For a full analysis of actual demographic statistics by region, see Appendix G.

Generally, respondents follow regional demographic trends (See Appendix H.2 for graphical comparisons between respondent-reported data and the actual regional DECD data) though tend to over-report being white, highly-educated, and having higher incomes than the regional median household income. Additionally, in all regions except Region D, female respondents are the majority.

Table 5: Average Respondent Reported Demographics by Region compared to Actual

		Region A	Region B	Region C	Region D
Actual Average HH Income (Pop. Weighted)		$109,332	$51,248	$86,991	$66,808
Respondent Reported HH Income ($1,000's)	$0-$50	5%	19%	12%	13%
	$50-$82	4%	23%	15%	13%

	$82-$115	14%	17%	18%	15%
	$115-$149	8%	17%	13%	14%
	$149-165	6%	2%	7%	7%
	$165+	42%	6%	20%	21%
Actual Ethnicity Composition	White	65%	43%	90%	74%
	Nonwhite	35%	57%	10%	26%
Respondent Reported Ethnicity	White	88%	79%	95%	89%
	Nonwhite	12%	21%	5%	11%
Actual Median Age		39	36	48	40
Respondent Reported Age Range	18-24	1%	2%	2%	5%
	25-30	4%	6%	1%	4%
	31-40	9%	9%	8%	10%
	41-50	17%	16%	14%	11%
	51-65	40%	44%	43%	38%
	65+	29%	23%	33%	31%
Actual Education Levels	Bachelors or More	70%	42%	63%	52%
	Less than Bachelors	30%	58%	37%	48%
Respondent Reported Education	Bachelors or More	92%	61%	75%	73%
	Less than Bachelors	8%	39%	25%	27%
Respondent Reported Gender	Female	53%	54%	57%	45%
	Male	47%	46%	43%	54%
Distance to Coast	More than 1 mile	72%	36%	51%	50%
	Less than 1 mile	28%	64%	49%	50%
FEMA	Yes	12%	10%	11%	8%
	No/ Not Sure	88%	90%	89%	92%

Table 5 also reports that on average, about 10% of respondents reported being in a FEMA flood zone. We compared respondent's addresses to FEMA hurricane surge inundation maps to confirm whether respondents would be impacted by storm surge and found that less than 2% of respondents fell within a Category 1 Hurricane surge inundation boundary. We therefore chose not to include this as a variable within our analysis and confirms that this study's primary focus is on inland residents of coastal towns.

3.2 Consequentiality

As previously discussed, consequentiality is contingent primarily on respondents caring about the impacts of at least some policies being proposed in a survey, and that they believe their response to be influential in the final outcome policy-makers could implement (Vossler, Doyon, & Rondeau, 2012). Table 6 summarizes the respondents' levels of concern about topics related to SLR and increased storms frequency.

Across all topics in Table 6 except for "Changes in high tide today," over 60% of respondents indicated that their level of concern was "Concerned" or higher. This indicates that most respondents care about the subject both in the near-term, and the long-term.

Table 6: Responses to Level of Concern Questions

	Not at all	Slightly	Somewhat	Moderately	Concerned	Very	Extremely
Impacts of coastal flooding on built assets today	5%	10%	12%	11%	26%	22%	13%
Impacts from coastal flooding on ecosystems today	4%	8%	9%	10%	24%	24%	22%
Change in storm frequency today	8%	7%	9%	12%	23%	24%	18%
Changes in high tide today	10%	9%	11%	14%	23%	19%	14%
Impacts on beaches and saltmarshes from hard infrastructure today	5%	7%	8%	12%	23%	23%	21%
Impacts of Coastal Flooding on Built Assets in 30 years	8%	7%	7%	9%	18%	24%	28%
Impacts from coastal flooding on ecosystems in 30 years	5%	7%	5%	7%	15%	26%	35%
Change in storm frequency in 30 years	8%	6%	5%	9%	16%	25%	31%
Changes in high tide in 30 years	8%	7%	5%	9%	18%	22%	30%
Impacts on beaches and saltmarshes from hard infrastructure in 30 years	6%	5%	6%	8%	17%	22%	35%

Additionally, we asked respondents the extent they believed the results of this study would be used by policy makers on a scale of "Not at all" to "Very much so." Table 7 below demonstrates that at least 50% of respondents believed this study would be used "Somewhat" or more by policy makers. Consistent with existing theory, which recommends a distinction between those who believe it is at least possible a link between the survey and policy exists, and those that believe otherwise is a satisfactory threshold for consequentiality, we conclude that respondents viewed our survey as consequential (Vossler & Watson, 2013).

Table 7: Extent respondents believe the results of this study will be used by policy-makers

	Percent	Cum.
Not at all	17%	17%
Slightly	31%	48%
Somewhat	35%	83%
Moderately	13%	96%
Very much so	4%	100%
Total	100%	

3.2.1 Drivers of Consequentiality

In order to understand how respondents' levels of concern about the topics covered in this survey influence perceived consequentiality, we conducted a simple linear regression, which we present in Table 8. Existing consequentiality research employs probit and ordered probit models to evaluate the binary situation of either "consequential" or "not," but here we review what other perceptions or held concerns would increase a respondent's answer on a Likert-Scale ranking of consequentiality (Vossler & Watson, 2013).

In Table 8, many of the concern-level variables corresponding to the questions in Table 6 (see Appendix B for reference) are shown to be statistically significant. For example, "FloodDamageBuildingsToday" and "FloodDamageEco30yrs" positively and significantly influence a respondent's belief that this survey will be used by policy-makers. For most of the concern-level variables, the higher a respondent rated their concern, the higher they rated the consequentiality of this survey.

Table 8: Drivers of Consequentiality in Coastal Choice Experiments

Prob>F	=	0.000
R^2	=	0.8723
Adj. R^2	=	0.8722

Extent this Survey will be Used by Policy Makers (scale of 1-5)	Coef.	Std. Err.	t	P<	[95% Conf. Interval]	
ImportanceCIRCA	0.0618473	0.005392	11.47	<0.001	0.051278	0.072417
PerceivedTownPropTax	0.0768493	0.005778	13.3	<0.001	0.065523	0.088175
PerceivedTownEduLevel	0.0972533	0.008141	11.95	<0.001	0.081297	0.11321
PerceivedTownInvolvement	0.1742944	0.008213	21.22	<0.001	0.158197	0.190392
ImportanceGovPubOpinion	0.0465929	0.005882	7.92	<0.001	0.035064	0.058122
TimeResident	0.0707239	0.007026	10.07	<0.001	0.056953	0.084495
PerceivedNoHomesAR	0.091282	0.00841	10.85	<0.001	0.074798	0.107766
FloodDamageBuildingsToday	0.1075666	0.012072	8.91	<0.001	0.083904	0.131229
FloodDamageEcoToday	-0.1553314	0.014117	-11	<0.001	-0.1830028	-0.12766
HighTideChangesToday	-0.0825014	0.008879	-9.29	<0.001	-0.0999	-0.0651
HumanImpactsEcoToday	0.0736386	0.012623	5.83	<0.001	0.048896	0.098382
FloodDamageBuilding30yrs	-0.0091536	0.012358	-0.74	0.459	-0.03338	0.015069
FloodDamageEco30yrs	0.2047116	0.016715	12.25	<0.001	0.171948	0.237476
StormFrequency30yrs	-0.0648507	0.015132	-4.29	<0.001	-0.09451	-0.03519
Region A	-0.0437457	0.028671	-1.53	0.127	-0.09994	0.012453
Region B	0.1186506	0.029136	4.07	<0.001	0.061541	0.17576
Region C	0.1155788	0.023177	4.99	<0.001	0.070149	0.161009

This study does not seek to deeply investigate these relationships, but this analysis helps contribute towards determining whether the survey was considered consequential or not.

3.4 Multinomial Logit Estimation Results

Prior to running our latent class model, we ran a multinomial logit in order to observe how the attributes affect choice regardless of unobservable attitudes. Given that status quo varied both across regions, and question types, we controlled for the effect of this variation through interactions by regional dummies, as well as interactions of demographic variables with the different types of status quo dummies. In order to achieve this parsimonious model, we performed a series of likelihood ratio tests to determine the significance. We found that when regional interactions with the five different status quo dummies were removed, a chi^2 value of 17.31 was produced with 15 degrees of freedom and a P-value of 0.3006. Table 9 summarizes the results below with robust standard errors. Variables significant at the 10% level are in bold.

Table 9: Multinomial Logit Regression Results

Std. Err. Adjusted for 909 clusters by respondent

Number of obs = 18,717

Log Likelihood = -10894.962

Wald chi2(51) = 2694.68

Prob > chi2 = 0.0000

Choice	Coef.	Std. Err.	z	P<	[95% Conf. Interval]	
0	(base outcome)					
1						
Choice Question Attributes						
At-risk homes bought out (000's)	**0.18365**	0.0543329	3.38	<0.002	0.0771594	0.2901406
At-risk homes protected (000's)	**0.1486624**	0.0274088	5.42	<0.001	0.0949421	0.2023827
At-risk saltmarsh lost (acres)	**-0.0006017**	0.0000659	-9.12	<0.001	-0.0007309	-0.0004724
At-risk beach lost (miles)	**-0.0475503**	0.0113618	-4.19	<0.001	-0.0698189	-0.0252816
Approval by Bought-out Homes (%)	**0.0019928**	0.001153	1.73	<0.085	-0.0002671	0.0042527
Fish/Shellfish Population Lost (%)	-0.0090199	0.0201751	-0.45	0.655	-0.0485624	0.0305225
Nuisance Flooding Days of Roads	**-0.0184585**	0.0035764	-5.16	<0.001	-0.0254682	-0.0114489
At-risk Homes Plan Contribution (%)	**0.0023693**	0.0011277	2.1	<0.037	0.0001591	0.0045795
Cost Attribute						
Change to household property tax ($1,000s)	**-1.237812**	0.0722585	-17.13	<0.001	-1.379437	-1.096188
Region A Interactions						
At-risk homes bought out (000's) * RegionA	**-0.1463831**	0.0583234	-2.51	<0.013	-0.2606949	-0.0320713
At-risk homes protected (000's)*RegionA	**-0.100523**	0.0258626	-3.89	<0.001	-0.1512127	-0.0498333
At-risk saltmarsh lost (acres)*RegionA	**-0.0102366**	0.0017843	-5.74	<0.001	-0.0137338	-0.0067395
At-risk beach lost (miles)*RegionA	**-0.2266876**	0.1339545	-1.69	<0.092	-0.4892337	0.0358584
Region B Interactions						
At-risk homes bought out (000's)*RegionB	**-0.1320716**	0.0583099	-2.26	<0.025	-0.2463568	-0.0177864
At-risk homes protected (000's)*RegionB	**-0.1239882**	0.0253634	-4.89	<0.001	-0.1736995	-0.0742769
At-risk saltmarsh lost (acres)*RegionB	**-0.0004093**	0.0002177	-1.88	<0.061	-0.0008359	0.0000173
At-risk beach lost (miles)*RegionB	**-0.0680145**	0.0321702	-2.11	<0.035	-0.1310669	-0.0049621
Region D Interactions						
At-risk homes bought out (000's)*RegionD	0.0882659	0.0941109	0.94	0.348	-0.0961879	0.2727198
At-risk homes protected (000's)*RegionD	-0.0135141	0.0361186	-0.37	0.708	-0.0843052	0.0572771
At-risk saltmarsh lost (acres)*RegionD	**-0.0045113**	0.0007494	-6.02	<0.001	-0.0059802	-0.0030424
At-risk beach lost (miles)*RegionD	**-0.3362552**	0.1180843	-2.85	<0.005	-0.5676963	-0.1048142
Choice Question Type Status Quo Dummies						
Type 1 SQ- No New Action	0.3337345	0.4205402	0.79	0.427	-0.4905092	1.157978
Type 2 SQ- Built Asset Focused	**0.5177125**	0.17667	2.93	<0.004	0.1714457	0.8639794
Type 3 SQ- Natural Asset Focused	**0.3673808**	0.1722113	2.13	<0.034	0.0298528	0.7049087

Type 2 Alt. Specific- Natural Assets Reset to No New Action	**-2.101803**	0.3498639	-6.01	<0.001	-2.787524	-1.416082
Type 3 Alt. Specific- Built Assets Reset to No New Action	**-1.453074**	0.2528491	-5.75	<0.001	-1.948649	-0.9574988
Status Quo Demographic Interactions- Type 1						
Type 1 SQ*LMI	**-0.4103284**	0.1872746	-2.19	<0.029	-0.7773799	-0.0432769
Type 1 SQ*High Income	**-0.4336731**	0.2145313	-2.02	<0.044	-0.8541467	-0.0131995
Type 1 SQ*Non-White	**0.508177**	0.2112504	2.41	<0.017	0.0941339	0.9222202
Type 1 SQ*Male	**0.6742757**	0.1437309	4.69	<0.001	0.3925683	0.9559831
Type 1 SQ*Low Education	0.1980648	0.1609861	1.23	0.219	-0.1174622	0.5135918
Status Quo Demographic Interactions- Type 2						
Type 2 SQ*LMI	-0.2692606	0.1729259	-1.56	0.119	-0.6081892	0.069668
Type 2 SQ*High Income	**-0.3868346**	0.190634	-2.03	<0.043	-0.7604702	-0.0131989
Type 2 SQ*Non-White	0.2349526	0.2032422	1.16	0.248	-0.1633948	0.6333
Type 2 SQ*Male	-0.1322538	0.121846	-1.09	0.278	-0.3710676	0.10656
Type 2 SQ*Low Education	0.2283513	0.1420692	1.61	0.108	-0.0500992	0.5068018
Status Quo Demographic Interactions- Type 3						
Type 3 SQ*LMI	-0.0420994	0.1725726	-0.24	0.807	-0.3803354	0.2961367
Type 3 SQ*High Income	**-0.3347987**	0.190871	-1.75	<0.080	-0.7088989	0.0393015
Type 3 SQ*Non-White	-0.0057507	0.192057	-0.03	0.976	-0.3821755	0.370674
Type 3 SQ*Male	**-0.2052897**	0.1226898	-1.67	<0.095	-0.4457572	0.0351778
Type 3 SQ*Low Education	0.217668	0.1439068	1.51	0.130	-0.0643842	0.4997203
Alternative Specific Option- Type 2						
Type 2 Alt. Specific*LMI	0.0706343	0.2257549	0.31	0.754	-0.3718372	0.5131058
Type 2 Alt. Specific*High Income	-0.0962873	0.2586783	-0.37	0.710	-0.6032875	0.4107129
Type 2 Alt. Specific*Non-White	0.2112558	0.2428752	0.87	0.384	-0.2647709	0.6872825
Type 2 Alt. Specific*Male	**0.4078816**	0.1650771	2.47	<0.014	0.0843364	0.7314267
Type 2 Alt. Specific*Low Education	0.0689289	0.1850272	0.37	0.709	-0.2937178	0.4315757
Alternative Specific Option- Type 3						
Type 3 Alt. Specific*LMI	-0.2572059	0.2108754	-1.22	0.223	-0.670514	0.1561023
Type 3 Alt. Specific*High Income	0.1232152	0.2268951	0.54	0.587	-0.3214911	0.5679214
Type 3 Alt. Specific*Non-White	0.2415176	0.2221776	1.09	0.277	-0.1939425	0.6769776
Type 3 Alt. Specific*Male	**0.4869142**	0.1503984	3.24	<0.002	0.1921388	0.7816897
Type 3 Alt. Specific*Low Education	-0.2398145	0.1830894	-1.31	0.190	-0.5986632	0.1190341

As this is a choice experiment study, our primary focus is on the signs and significance of the attribute parameters and their role in explaining the probability that an individual chooses a particular management plan in a set of proposed plans to maximize their utility. This model involves interactions between dummy variables for each region. Region C is omitted as the reference region so that the initial coefficients in Table 9 comprise the utility model for respondents in Region C. Interaction terms with a dummy variable indicating a respondent is from one of the other regions are added to these initial coefficients to create the comparable coefficients for another region. The coefficients on interaction terms therefore represent the difference between the estimate for the corresponding region and the estimate for the reference-region, C. This is made apparent in Equation 7 below.

Likewise, in standard CEs with just one status quo, one would interact any demographic indicators with just that single status quo. In our model, given the different status quos available as baselines for respondents, we interact each status quo dummy variable, coded 1 or 0, with demographic variables. The demographic variables interacted on status quo were selected using likelihood ratio tests of the null hypothesis that the unconstrained model will be better fitting than a constrained model. The unconstrained model included what would appear to be "dummy trap" coefficients for ethnicity and income where there were dummies for both the respondent being white (white=1) and nonwhite (nonwhite=1), and the respondent being low-to-moderate income (LMI) (LMI=1) or high income (high income=1). This appearance occurs because there were high numbers of non-response data or "Not Willing to Answer" responses to these questions, which would result in that observation being dropped. In order to prevent those responses from unnecessarily being ignored, we created a third dummy category each for income and ethnicity to capture those values. Ultimately, testing showed that a more parsimonious model did not include coefficients for being white, due to the majority of respondents being white.

Our resulting utility function of respondent *n* for choice option *i* is as follows, with dummy variables indicated by bold font:

$$(7) \quad V_i = \beta_n(\mathbf{Type1SQ}) + \beta_{sq2}(\mathbf{Type2SQ}) + \beta_{sq3}(\mathbf{Type3SQ}) + \beta_{T2asp}(Type2AltSpc) + \beta_{T3asp}(Type3AltSpc) + \beta_C(\text{HouseholdPropertyTax}) + \beta_{HomesBought}(\text{AtRiskHomesBoughtOut}) + \beta_{HomesProtected}(AtRiskHomesProtected) + \beta_{Approval}(\text{ApprovalBoughtOutHomes}) + \beta_{Saltmarsh}(\text{SaltmarshQuantityLost}) + \beta_{Beach}(\text{BeachQuantityLost}) + \beta_{Fish}(FishPopLost) + \beta_{Road}(\text{RoadFloodingDays}) + \beta_{Share}(AtRiskHomesPlanContr) + \beta_{HomesBoughtA}(\text{AtRiskHomesBoughtOut} * \mathbf{regiona}) + \beta_{HomesProtectedA}(AtRiskHomesProtected * \mathbf{regiona}) + \beta_{SaltmarshA}(\text{SaltmarshQuantityLost} * \mathbf{regiona}) + \beta_{BeachA}(\text{BeachQuantityLost} * \mathbf{regiona}) + \beta_{HomesBoughtB}(\text{AtRiskHomesBoughtOus} * \mathbf{regionb}) + \beta_{HomesProtectedB}(AtRiskHomesProtected * \mathbf{regionb}) + \beta_{SaltmarshB}(\text{SaltmarshQuantityLost} * \mathbf{regionb}) + \beta_{BeachB}(\text{BeachQuantityLost} * \mathbf{regionb}) + \beta_{HomesBoughtD}(\text{AtRiskHomesBoughtOut} * \mathbf{regiond}) + \beta_{HomesProtectedD}(AtRiskHomesProtected * \mathbf{regiond}) + \beta_{SaltmarshD}(\text{SaltmarshQuantityLost} * \mathbf{regiond}) + \beta_{BeachD}(\text{BeachQuantityLost} * \mathbf{regiond}) + \beta_{sq1lmi}(\mathbf{Type1SQ} * \mathbf{LMI}) + \beta_{sq2lmi}(\mathbf{Type2SQ} * \mathbf{LMI}) + \beta_{sq3lmi}(\mathbf{Type3SQ} * \mathbf{LMI}) + \beta_{T2Aslmi}(\mathbf{Type2AltSpc} * \mathbf{LMI}) + \beta_{T3Aslmi}(\mathbf{Type3AltSpc} * \mathbf{LMI}) + \beta_{sq1nonwhite}(\mathbf{Type1SQ} * \mathbf{Nonwhite}) + \beta_{sq2nonwhite}(\mathbf{Type2SQ} * \mathbf{Nonwhite}) + \beta_{sq3nonwhite}(\mathbf{Type3SQ} * \mathbf{Nonwhite}) + \beta_{T2ASnonwhite}(\mathbf{Type2AltSpc} * \mathbf{Nonwhite}) + \beta_{T3ASnonwhite}(\mathbf{Type3AltSpc} * \mathbf{Nonwhite}) + \beta_{sq1male}(\mathbf{Type1SQ} * \mathbf{male}) + \beta_{sq2male}(\mathbf{Type2SQ} * \mathbf{male}) + \beta_{sq3male}(\mathbf{Type3SQ} * \mathbf{male}) + \beta_{T2ASmale}(\mathbf{Type2AltSpc} * \mathbf{male}) + \beta_{T3ASmale}(\mathbf{Type3AltSpc} * \mathbf{male}) + \beta_{sq1edu}(\mathbf{Type1SQ} * \mathbf{LowEducation}) + \beta_{sq2edu}(\mathbf{Type2SQ} * \mathbf{LowEducation}) + \beta_{sq3edu}(\mathbf{Type3SQ} * \mathbf{LowEducation}) + \beta_{T2ASLowedu}(\mathbf{Type2AltSpc} * \mathbf{LowEducation}) + \beta_{T3ASLowedu}(\mathbf{Type3AltSpc} * \mathbf{LowEducation}) + \varepsilon_{ni}$$

Attributes related to human-built assets, “At-risk Homes Bought Out”, “At-risk Homes Protected”, “Approval by Bought Out Homes”, and “At-risk Homes Plan Contribution”, are positive attributes with statistical significance. As these attributes represented a positive change of goods, at-risk homes that would either be protected or removed, the proportional share of the plan’s cost by these homes, and the proportion of bought-out homes that voluntarily accepted the offer, we would expect their sign to be positive as well. When a variable’s coefficient is positive, it indicates that an increasing change from the status quo for that variable also increases the benefit to the respondent, and therefore the probability that they would choose an option with that increased variable.

Similar results were achieved for the standard set of Choice Question environmental attributes which indicated a negative change in the provision of goods (“bads,” in this case), and all had negative coefficients. These attributes represented a change away from the no-action status quo levels of the attribute which, here, is the loss of natural resources (salt marsh, beaches, and fish/shellfish) due to SLR. Because decreased provision means a “decrease in the loss of” these attributes, benefit increases with the decreased provision.[7] The coefficients are relatively small because they represent the marginal utility for units of one acre of saltmarsh, one mile of beach, and one per cent of fish population, as opposed to our built asset coefficients which use units of “thousand homes”.

Lastly, consistent with theory and expectations, our coefficient for cost to the respondent, “Change to household property tax” is statistically significant and has a negative value,

[7] The attribute for fish and shellfish was not shown to be statistically significant on its own, but likelihood ratio testing confirmed its inclusion in the model produced a more significant model.

indicating the higher the cost, the less likely the respondent will choose the corresponding alternative.

Our approach to measuring the value of the status quo dummy variable, given the differing baselines, produces coefficients that generally support the logic that a status quo will typically be undesirable if the alternatives provide more benefit to the respondent. Here, “Type 1 SQ- No New Action” represents the no-action status quo if there is no new action and takes a positive coefficient but is not significant.[8] However, the “Type 2” and “Type 3” Alternative Specific Constants, which are coastal management plans that include some attributes that are reverted to their no-action levels meaning these choices partially represent the “Type 1 SQ- No New Action”, are each highly significant and carry negative coefficients. The negative coefficients on these variables indicate that while the “Type 1 SQ- No New Action” is not significant, when the no-action levels of attributes are included in a plan where the other attributes do not change, they decrease utility (See Appendices A-2 and A-3 for examples of these questions). In other words, when a respondent is comparing a “Type 2” “Current Plan” with a “Type 2” “Alternative Plan” that includes no-action level attributes, the “Alternative Plan” will provide them a decreased utility level.

For the “Type 2” and “Type 3” status quos, the coefficients are statistically significant and take on positive values. “Type 2” and “Type 3” status quos are always different from the no-action status quo and most attributes have a higher provision than taking no new action, we would expect this result because the initial utility with some action may, for the average person, be higher than the initial utility with all attributes at their no-action status quo levels.

[8] However, it is statistically significant when robust standard errors are not use.

Additionally, by including regional interactions on the attributes that varied by region, we can consider differences in how living in a certain region may affect a respondent's willingness to pay for a certain attribute. For example, with Region C serving as the reference, buying out homes and removing them to allow for saltmarsh and habitat expansion provides positive utility. But, in the model above, if the respondent lives in Region A, the effect of interacting Region A on the quantity of homes is negative. When the two effects are combined, we find that living in Region A reduces the utility of buying out homes.

Despite our likelihood ratio test indicating the significance of this model, there are still multiple insignificant variables in this equation, and the interactions of select variables with region do not suggest a particular pattern in why respondents in those regions may make certain choices, beyond preferences for certain attributes stated in the choice questions. In the following sections, we apply latent class modeling to attempt producing greater discrimination of what drives individual preferences.

3.3 Principal Component Analysis

Our survey contained four sets of Likert scale questions that addressed respondents' levels of concern or subjective importance levels related to coastal topics (see Appendix B for a summary of these questions). Likert scale questions can be analyzed to measure attitudes towards specific topics, by using Principal component analysis (PCA) to identify individuals who answer Likert scale questions in a similar pattern. The assumption is that the response patterns of individuals in these questions will be collinear. In order to reduce the dimensions of our Likert scale questions into a more parsimonious set of attitude scales, we performed a Principal component analysis (PCA) (Jackson, 1991).

The initial correlation test confirmed that many of the 43 Likert Scale question variables were highly correlated with each other (see Appendix B as a reference for these variables). The variables with the highest correlation were expected, such as level of concern over the impacts on natural coastal assets from man-made shoreline hardening now versus 30 years from now, or the importance of developing coastal land so that wildlife habitat is protected versus the level of concern over the impacts from coastal flooding on local ecosystems.

Geometrically, PCA rotates the orthogonal regression (i.e. axis) line about the means of the observations in order to transform correlated variables into a set of new uncorrelated variables (Jackson, 1991). The PCA finds the eigenvalues of the correlation matrix of the 43 Likert scale questions variables, creating an equal number of individual eigenvectors (i.e. factor scores) as there are variables. Each of these individual eigenvectors are components that are normalized to a mean of zero and a standard deviation of one.

Our PCA generated seven principal components with an eigenvalue greater than one with the diminishing range of resulting eigenvalues shown by Figure 2. The maximum eigenvalue produced by the PCA was equal to 13.6077 (see Appendix F). The eigenvalues are the sum of the variance of the Likert scale question variables (i.e. total variance), which allows us to determine how much of the total variance is explained by a principal component. Using a threshold eigenvalue of two, we were left with five components which contain more than 62% of the variance in responses to the Likert scale questions (Table 11). Additionally, each component has a unique set of eigenvectors on the set of 43 Likert Scale question variables (Table 10). In studies with smaller sets of attitudinal questions (i.e. Likert Scale questions) than ours, a factor score threshold of 0.4 or so is used to identify which scores to use in indicating the sentiment a component represents (Kafle, Swallow, & Smith, 2015).[9] Given our large number of Likert Scale variables, the threshold for our factor scores was lowered to 0.3, though larger weights that do not quite meet that threshold are consistent with the interpretation of the components (e.g. FloodDamageEco30yrs in Component 1). Table 10 summarizes those groupings, with each component's primary factor scores in bold font.[10]

Figure 2: Scree Plot of Eigenvalues after PCA

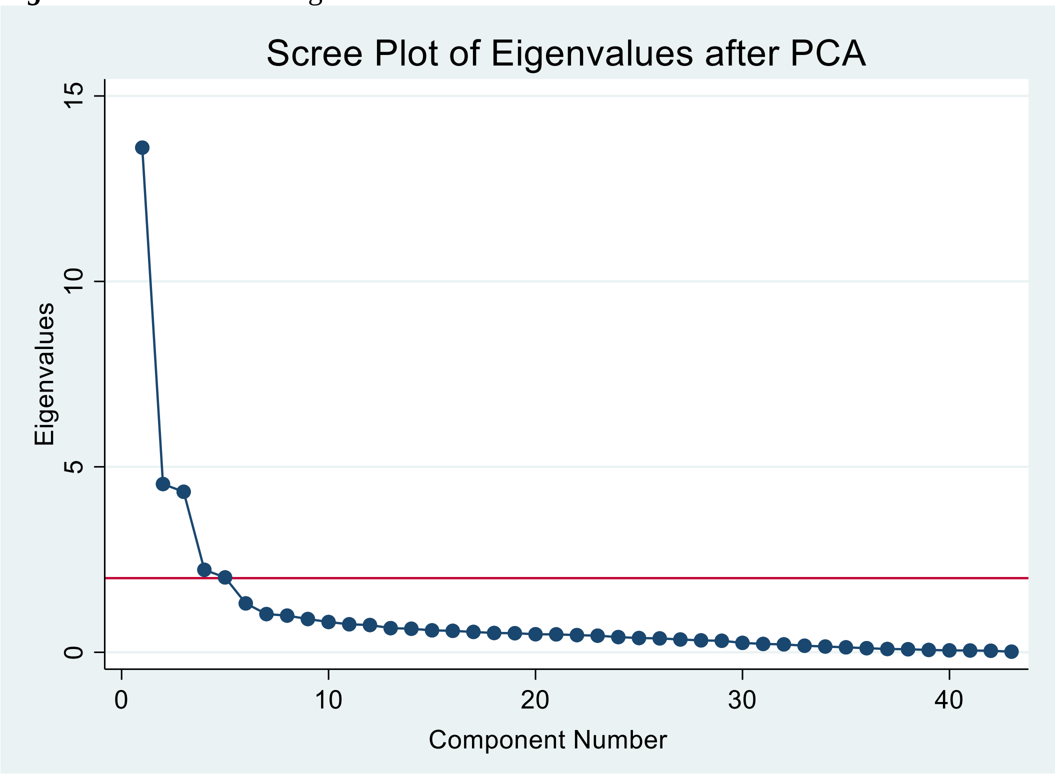


Table 10: Principal Component Analysis Rotated Components

Variable	Comp. 1 **Coastal Flooding**	Comp. 2 **Pro-Coastal Wildlife**	Comp. 3 **Pro-Public Access**	Comp. 4 **Altruism**	Comp. 5 **Pro-Coastal Recreation**	Unexplained
FloodDamageBldgToday	**0.3224**	-0.0842	0.0156	0.0266	0.0329	0.3269
FloodDamageEcoToday	0.2659	0.0980	-0.0129	-0.0271	-0.0224	0.2591
StormFrequencyToday	**0.3268**	-0.0171	-0.0321	0.0140	0.0143	0.2654
HighTideChangesToday	**0.3334**	-0.0000	-0.0451	-0.0039	0.0458	0.217

[9] Other studies that integrate Likert Scale questions with PCA do not typically have this many questions, usually using 10 to 20.
[10] For a description of each attribute included in Table 10, see Appendix B.

HumanImpactsEcoToday	0.2839	0.0534	-0.0073	-0.0327	-0.0204	0.3046
FloodDamageBldg30yrs	**0.3392**	-0.0767	0.0312	0.0158	0.0083	0.2391
FloodDamageEco30yrs	0.2906	0.0771	0.0109	-0.0141	-0.0466	0.1621
StormFrequency30yrs	**0.3335**	-0.0047	-0.0088	0.0080	-0.0117	0.1867
HighTideChanges30yrs	**0.3391**	-0.0064	-0.0116	0.0109	0.0067	0.1583
HumanImpactsEco30yrs	0.2958	0.0577	0.0153	-0.0220	-0.0461	0.1957
PrvtMgmtPublicAccess	0.0185	0.0860	0.2922	0.0079	-0.0929	0.3989
PrvtDevelopPublicAccess	0.0232	0.2568	0.152	0.0147	-0.1564	0.2236
CoastalHabitatMaintained	0.0155	0.2638	0.1377	-0.0104	-0.1253	0.2622
PropertyDevelopRights	0.0248	-0.1699	0.1022	-0.0452	0.1984	0.7589
PublicOpinion	0.0159	-0.0174	0.2901	0.0037	-0.0444	0.619
TouristAccess	-0.0057	-0.0387	**0.3591**	-0.0083	0.0018	0.4429
WildlifePublicAccess	0.0237	-0.2271	0.2733	-0.0672	0.1842	0.5183
ReplaceNaturalAssets	0.0071	0.0667	0.1982	0.0300	-0.0691	0.7047
RestrictedAccessWildlife	0.0168	0.2632	0.0902	-0.0059	-0.1202	0.3767
LocalCoastalEconomy	0.0428	-0.1451	0.2852	0.0016	0.1386	0.5274
ContributeCoastProtection	0.0007	0.1460	0.1985	0.0035	-0.0642	0.5272
PublicCoastalAccess	-0.0377	0.0085	**0.3928**	-0.0093	-0.0301	0.3105
RespondentCoastalAcccess	-0.0368	0.0582	**0.3409**	0.0156	-0.0111	0.3405
RespondentPrivateAccess	-0.0272	0.0231	0.1442	0.0251	0.1504	0.7171
PublicBeachesImportance	-0.0064	0.0530	0.1853	0.0637	0.0996	0.5938
PrivateBeachesImportance	0.0162	0.0411	-0.1298	0.0400	**0.3042**	0.6891
EndSpeciesImportance	0.0141	**0.3157**	-0.0107	0.0106	0.0167	0.3263
FishingAccessImportance	-0.0029	0.0810	-0.0305	-0.0458	**0.3480**	0.5249
CoastalBusinessImportance	0.0446	-0.0579	0.0898	0.0508	**0.3149**	0.4777
LocalCharmImportance	0.0106	0.0442	0.1250	0.0250	0.2174	0.5572
DunesImportance	-0.0033	0.2863	-0.0608	-0.0287	0.1394	0.4467
WildlifeHabitatImportance	-0.0122	**0.3483**	-0.0307	0.0022	0.0839	0.2297
TidalMarshImportance	0.004	**0.3341**	-0.035	-0.0355	0.0921	0.2584
BoatAccessImportance	-0.0308	0.0410	-0.0512	-0.0171	**0.4074**	0.4406
KayakAccessImportance	-0.0129	0.1417	-0.0087	-0.0268	0.2998	0.4968
CoastalRoadImportance	0.0228	-0.0658	0.0944	0.0207	**0.3164**	0.5238
UndevelCoastImportance	-0.0228	**0.3366**	-0.0234	0.0116	0.0612	0.3135
HistoricSiteImportance	-0.0086	0.2213	0.0445	0.0115	0.1306	0.4775
PublicAidVeryLowIncome	0.0127	-0.0127	0.0521	**0.4346**	-0.0637	0.1839
PublicAidLowIncome	0.0097	-0.0023	0.0350	**0.4537**	-0.0506	0.1263
PublicAidMiddleClass	-0.0048	0.0008	0.0082	**0.4772**	-0.0102	0.06087
PublicAidUpperMidClass	-0.0102	0.0044	-0.0486	**0.4533**	0.0560	0.1474
PublicAidWealthy	-0.001	0.0095	-0.0866	**0.3799**	0.0949	0.3659

Table 11: Principal Component/Correlation

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1- Coastal Flooding	13.7083	9.22805	31.88%	31.88%
Comp2- Pro- Coastal Wildlife	4.48024	0.179598	10.42%	42.3%

Comp3- Pro-Public Access	4.30065	2.04893	10%	52.3%
Comp4- Altruism	2.25172	0.217948	52.4%	57.54%
Comp5- Pro-Coastal Recreation	2.03377	0.726798	4.73%	62.27%

3.3.1 Component 1- Coastal Flooding

Component 1 contained the variables “FloodDamageBldgToday” (level of concern about the effects of coastal flooding on buildings in the very near-term), “StormFrequencyToday” (concern about changes in the frequency of severe storms in the very near-term), “HighTideChangesToday” (concern about changes in local high tide level in the very near-term), “FloodDamageBldg30yrs” (level of concern about the effects of coastal flooding on buildings in 30 years), “StormFrequency30yrs” (concern about changes in the frequency of severe storms in 30 years), and “HighTideChanges30yrs” (changes in local, coastal high tide levels in 30 years). These results demonstrate that generally, someone who has high concern about the effects of coastal flooding in the near term, is also concerned about flooding effects on buildings in the long term, and about the level of regular flooding. Therefore, a higher value for component 1’s factor score indicates that the individual has a higher level of concern about the present and future effects of coastal flooding. We refer to this component as “Coastal Flooding”.

3.3.2 Component 2- Pro-Coastal Wildlife

Component 2 contained the variables “EndSpeciesImportance” (importance level of endangered species to the respondent), “WildlifeHabitatImportance” (importance of fish and wildlife habitat as a resource to the respondent), “TidalMarshImportance” (the importance level of tidal marshes as a resource to the respondent) and “UndevelCoastImportance” (the importance level of undeveloped coastline to the respondent). These results demonstrate that generally, a respondent who indicates high importance of restricting access to coastal land to protect wildlife also would indicate high resource importance of endangered wildlife, wildlife habitat, and reserving some portion of coastline to leave undeveloped. Therefore, a higher value for component 2's factor score indicates that the individual has a higher level of concern related to coastal wildlife. We refer to this component as "Pro-Coastal Wildlife".

3.3.3 Component 3- Pro-Public Coastal Access

Component 3 contained the variables "TouristAccess (the importance level of tourists being able to access the shore), "PublicCoastalAccess" (the importance level of public access to the coast), and "RespondentCoastalAccess" (the importance of the respondent being able to visit, observe, or photograph the coast). This variable grouping demonstrates that generally, a respondent who indicates high importance to managing development to ensure public access will also indicate high importance of public access, tourist access, and personal access to the shore. Therefore, a higher value for component 3's factor score indicates that the individual has a higher level of concern related to public coastal access. We refer to this component as "Pro-Public Coastal Access".

3.3.4 Component 4- Altruism

Component 4 contained the variables "PublicAidVeryLowIncome", "PublicAidLowIncome", "PublicAidMiddleClass", "PublicAidUpperMidClass", and "PublicAidWealthy", which all indicated how deserving coastal households of different income levels were of public funds for defense against coastal flooding and help with repairs for coastal flooding damages. This grouping demonstrates that generally, a respondent that thinks very low-income coastal households deserve public aid also thinks that a wealthy coastal household deserves aid. Therefore, a higher value for component 4's factor score indicates that the individual favors public assistance for people living on the coast that are at-risk of flood damage regardless of their income. We refer to this component as "Altruism".

3.3.5 Component 5- Pro-Coastal Recreation

Component 5 included the variables "PrivateBeachImportance" (the importance level of private beaches as a resource to the respondent), "FishingAccessImportance" (the importance level of fishing access as a resource to the respondent), "CoastalBusinessImportance" (the importance level of coastal businesses as a resource to the respondent), "BoatAccessImportance" (the importance level of motor boat access as a resource to the respondent), and "CoastalRoadImportance" (the importance level of coastal roadways as a resource). We interpreted this as generally, a respondent who finds fishing access very important will also find boating, coastal businesses and roads along the coast important. Therefore, a higher value for component 5's factor score indicates that the individual favors coastal recreation resources. We refer to this component as "Pro-Coastal Recreation".

3.5 Latent Class Modeling

3.5.1 Identifying the number of Classes

In the latent-class economic literature, information criteria scores are the consensus tool for determining the number of latent classes that significantly improve model fit. Standard likelihood ratio tests used in multinomial logit models cannot exist because the discrete nature of increasing the number of classes violates the assumptions need to prove the statistic is chi-squared distributed (Breffle, Morey, & Thacher, 2011). The consensus criteria to determine preferred models is based on goodness of fit indicators such as Bayesian Information Criteria (BIC) and Akaike Information Criteria (AIC) (Swait, 2007). For our model both AIC and BIC indicated a solution with two classes was preferred. There tends to be consensus that parsimony is preferred, particularly in such a complex framework. We look for significant estimates in the class allocation model to confirm the better fitting model is also consistent with behavioral models (Hoyos, Mariel, & Hess, 2015).

3.5.2 Two-Class Model

Our original intention was to have an LCM that used the same variables as included in our multinomial logit model but was able to cluster survey individual survey respondents into latent classes based on a set of indicator variables in the class membership mode. The number of classes would be determined by the AIC and BIC.

We were able to produce a two-class LCM that included the regional interactions consistent with our multinomial logit model that produced statistically significant coefficients for each class, shown in Table 12 (statistically significant coefficients at the 10%, 5% and 1% levels are all indicated by bold font). However, this model was unable to converge for any C>2. Non-convergence in LCM has been shown to be influenced by sample size, indicator variable quality, covariate effect size, and number of dummy variables (Wurpts & Geiser, 2014). Our model includes five principal component covariates and seven dummy variables, and it is possible that our sample size is not large enough to support a model with greater than two classes. If a minimum sample size threshold is not achieved, as additional classes are added to a model, so do the number of estimated parameters which can cause data sparseness to occur (Wurpts & Geiser, 2014). We report the results of this model as the model that contains independent variables that significantly contribute to respondent choice selection in a two-class model. This model is statistically insignificant from the unrestricted model, which was tested by restricting sets of coefficients in the unrestricted model and using likelihood ratio tests to determine their significance. By removing variables that were not significant at least at the 20% level, we produced this parsimonious model that is statistically insignificant from the unrestricted model.

Table 12: 2-Class Latent Class Model

Log Likelihood = -4386.2181								
	Class 1- 71% Share				*Class 2- 29% Share*			
Choice	Coef.	Std. Err.	z	P<	Coef.	Std. Err.	z	P<
At-risk homes bought out (000's)	**0.3402511**	0.071976	4.73	<0.001	**-0.7520195**	0.244361	-3.08	<0.003
At-risk homes protected (000's)	**0.2256254**	0.045498	4.96	<0.001	**-0.3791432**	0.132287	-2.87	<0.005
At-risk saltmarsh lost (acres)	**-0.0006392**	9.55E-05	-6.7	<0.001	-0.0002438	0.000288	-0.85	0.398
At-risk beach lost (miles)	-0.0095391	0.019199	-0.5	0.619	-0.0115459	0.060049	-0.19	0.848
Approval by Bought-out Homes	**0.0059888**	0.002176	2.75	<0.007	**-0.0103335**	0.006257	-1.65	<0.010
Fish/Shellfish Population Lost (%)	0.0009551	0.002006	0.48	0.634	**-0.0376888**	0.019234	-1.96	<0.051
Nuisance Flooding Days of Roads	**-0.0077677**	0.004306	-1.8	<0.072	**-0.0335654**	0.01387	-2.42	<0.017
At-risk Homes Plan Contribution (%)	**0.0059969**	0.001968	3.05	<0.003	0.000259	0.005732	0.05	0.964
Change to household property tax ($)	**-1.014992**	0.090433	-11.2	<0.001	**-1.965956**	0.255754	-7.69	<0.001
Type 1 SQ- No New Action	**-1.673737**	0.395472	-4.23	<0.001	-0.435996	0.910809	-0.48	0.632
Type 2 SQ- Built Asset Focused	**-0.4833514**	0.093521	-5.17	<0.001	**2.024036**	0.329011	6.15	<0.001
Type 3 SQ- Natural Asset Focused	**-0.1874751**	0.096898	-1.93	<0.054	**2.085314**	0.371929	5.61	<0.001
Type 2 Alt. Specific- Natural Assets Reset to No New Action	**-2.110918**	0.155551	-13.6	<0.001	0.2937661	0.497759	0.59	0.555
Type 3 Alt. Specific- Built Assets Reset to No New Action	-0.1473183	0.447526	-0.33	0.742	**-2.913745**	1.227387	-2.37	<0.019
Region A Interactions								
At-risk homes bought out (000's) * RegionA	**-0.2564672**	0.070678	-3.63	<0.001	**0.5183359**	0.250415	2.07	<0.039
At-risk homes protected (000's)*RegionA	**-0.1428743**	0.038653	-3.7	<0.001	**0.1957572**	0.110061	1.78	<0.076
At-risk saltmarsh lost (acres)*RegionA	**-0.0124876**	0.002217	-5.63	<0.001	-0.0063469	0.007562	-0.84	0.401
At-risk beach lost (miles)*RegionA	-0.0967036	0.238218	-0.41	0.685	0.3022442	0.607273	0.5	0.619
Region B Interactions								
At-risk homes bought out (000's)*RegionB	**-0.228998**	0.071846	-3.19	<0.002	**0.5391184**	0.240182	2.24	<0.026
At-risk homes protected (000's)*RegionB	**-0.197762**	0.039854	-4.96	<0.001	**0.2936046**	0.112847	2.6	<0.010
At-risk saltmarsh lost (acres)*RegionB	**-0.0007602**	0.000369	-2.06	<0.041	0.0000842	0.000802	0.1	0.916
At-risk beach lost (miles)*RegionB	**-0.1663139**	0.054029	-3.08	<0.003	**-0.2219461**	0.122883	-1.81	<0.072
Region D Interactions								

At-risk homes bought out (000's)*RegionD	**0.2582536**	0.112333	2.3	<0.023	0.361391	0.345402	1.05	0.295
At-risk homes protected (000's)*RegionD	**0.0910283**	0.051184	1.78	<0.076	**-0.3416969**	0.121752	-2.81	<0.006
At-risk saltmarsh lost (acres)*RegionD	**-0.0046331**	0.001089	-4.25	<0.001	-0.0004365	0.002889	-0.15	0.880
At-risk beach lost (miles)*RegionD	**0.5566911**	0.224192	2.48	<0.014	**-1.044107**	0.568767	-1.84	<0.067
Class 1 Membership								
PC1- Coastal Flooding	**0.2909931**	0.042821	6.8	<0.001				
PC2- Pro-Coastal Wildlife	0.0724994	0.05022	1.44	0.149				
PC3- Pro-Public Coastal Access	-0.0298876	0.053591	-0.56	0.577				
PC4- Altruism	**0.1294019**	0.05079	2.55	<0.012				
PC5- Pro-Coastal Recreation	**-0.1476885**	0.054362	-2.72	<0.008				
Region A	0.0744006	0.290483	0.26	0.798				
Region B	**-0.5279859**	0.283717	-1.86	<0.064				
Region D	-0.226273	0.241858	-0.94	0.349				
Income LMI	0.252538	0.199619	1.27	0.206				
Non-White	**-0.6173777**	0.300561	-2.05	<0.041				
Male	**-0.3223538**	0.19126	-1.69	<0.093				
Low Education	**-0.4378418**	0.219288	-2	<0.047				
_cons	**1.412526**	0.236057	5.98	<0.001				

Table 13: 2-Class Model Information Criteria

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
2-Class Model	15,855	.	-4386.218	65	8902.436	9,401.07

Post-estimation of AIC and BIC are reported in Table 13.

As in the multinomial logit model (Table 9), the LCM provides coefficients on the choice question attributes for each class, and on the sets of regional interaction coefficients which represent the difference between the estimate for the corresponding region and the estimate for the reference-region, C. Additionally, we again include the three types of status quo dummies, as well as dummies for “Type 2” and “Type 3” alternative specific constants which return subsets of attributes to no-action status quo levels.

Results in Table 12 indicate heterogeneous preferences in relation to the various status quos between the two classes. The membership model incorporates the principal component score covariates, dummies on region (with Region C as the reference region), and demographic variables on income, gender, ethnicity, and education, distributing 71% of respondents into Class 1, and 29% into Class 2 (Table 12). Principal Components 1- Coastal Flooding and 4- Altruism have high statistical significance and positively influence the probability of a respondent being in Class 1. However, Component 5- Pro-Coastal Recreation has a statistically significant negative effect, as does being Non-white, having less than a bachelor’s degree, being male, and living in Region B (though effects from male and Region B are less significant).

Class 1’s corresponding choice model includes a large, negative effect with high statistical significance on “Type 1 SQ- No New Action”, indicating that taking absolutely no action against SLR will have significant, negative impacts for respondents in Class 1. The “Type 2 SQ-Built Asset Focused” and “Type 3 SQ- Natural Asset Focused” coefficients were also found to be highly significant and negative, though their coefficients were smaller than "Type 1 SQ- No New Action" meaning respondents in Class 1 generally found the "Current Plan" options in "Type 2" and "Type 3" questions to be undesirable, though more desirable than the no action status quo option provided in "Type 1". The largest statistically significant negative impact from a choice option was for "Type 2 Alt. Specific- Natural Assets Reset to No New Action" where some action was taken related to built assets but would allow natural assets to revert to no-action status quo levels.

However, before regional effects are accounted for, the model shows that the only statistically significant coefficient on a natural asset is on saltmarsh. Given that Region C is our reference, we find that beach loss is only significant in Regions B and D for respondents in Class 1, while salt marsh loss is significant in all regions.

"At-risk Homes Bought out", "At-risk Homes Protected", and "Approval by Bought-out Homes", each have positive coefficients indicating that for an individual in Class 1, each unit of at-risk homes that are bought out and removed or protected in place provides positive utility. Within each region, we find that a respondent in Class 1 and that lives in Region D would have the overall highest utility on the protection or buying out of at-risk households.

Alternatively, for respondents in Class 2 (the reference class for membership), while we also find that "Type 1 SQ- No New Action" is negative, it is not significant, and "Type 2 SQ-Built Asset Focused" and "Type 3 SQ- Natural Asset Focused" coefficients had large, positive and statistically significant impacts.

Coefficients on built assets ("At-risk Homes Bought out", "At-risk Homes Protected", and "Approval by Bought-out Homes") were statistically significant, and in contrast to Class 1, were negative, though these coefficients are adjusted upward by some regions to create smaller negative effects. Additionally, coefficients on beach loss and saltmarsh were found to be negative, though not significant, except in the case of fish and shellfish population loss. Effects from the cost to the respondents in both classes ("Change to household property tax") was found to be negative and statistically significant, though was nearly double in Class 2. We can interpret this as members of Class 2 having a stronger aversion to contributing funds for any type of plan. Additionally, members of Class 2 had large, positive, and statistically significant at the 1% level coefficients on "Type 2 SQ-Built Asset Focused" and "Type 3 SQ- Natural Asset Focused" attributes, meaning that members of Class 2 receive greater utility from plans that provide some set of actions related to coastal management when they come at no cost to the respondent. We find that Class 2 consists of members whose preferences are not necessarily in support of no action, but rather that action should be taken using existing public funds and should not require additional tax revenue to accomplish some change from the no-action status quo levels.

3.5.2 Comparison of the Multinomial Logit Model to the Latent Class Models

Willingness to pay is generally calculated as:

(8) $$WTP = \frac{U_{noaction} - U_i}{\beta_P}; \qquad U_{noaction} \neq U_i$$

where the utility estimate a plan is subtracted from the utility estimate for no action, and then divided by the estimated cost coefficient provided by the model. After calculating WTP for each of the models, we can compare differences in estimated WTP across the classes and models (see Table 14). For the latent class model, the estimates for Class 1 and Class 2 generally align with the findings in our model; Class 1 has a high WTP for an action-taking plan, while Class 2 has a negative WTP (i.e. willingness to accept) these plans as they do not want to pay for any kind of plan. Additionally, there is clear regional variation in WTP. Region A and C show the highest WTP for this particular plan (which is the same plan, adjusted to each regions attribute levels), which could be expected given that Region A is the wealthiest region (Table 5), and Region C had the highest amount of participation, and the second highest income levels (Table 5). Additionally, Region C has recently shown to have a high level of activism on the topic of coastal management. However, we note that these estimates are higher than the levels provided in the choice questions, but as we only compare on this one plan, it is unclear if it is just this particular plan provides high WTP estimates.

We expected that the share-weighted average of these estimates would be approximately equal to our Multinomial Logit estimates. However, as shown by Table 14, this is not the case. This could be an indication that an LCM with more than two classes would better estimate different classes based on underlying preferences, and the weighted average of those class shares would provide a WTP closer to the Multinomial Logit model.

Table 14: Sample Plan Willingness to Pay Estimates by Region and Model

	Region A			
	MNL	LCM-Class 1	LCM-Class 2	LCM-Weighted Avg.
Utility Value of No Action Status Quo	-1.3392986	-2.9049753	-2.0242951	-2.649578
WTP Estimates For Sample Plan Where:	$1,047	$3,938	-$1,083	$2,482
At-risk homes bought out (000's)= 1				
At-risk homes protected (000's)= 11				
At-risk saltmarsh lost (acres)= 33				
At-risk beach lost (miles)= .2				
Approval by Bought-out Homes= 80%				
Fish/Shellfish Population Lost (%)= 5%				
Nuisance Flooding Days of Roads= 22				
At-risk Homes Plan Contribution (%)= 40%				
	Region B			
	MNL	LCM-Class 1	LCM-Class 2	LCM-Weighted Avg.
Utility Value of No Action Status Quo	-1.2033333	-3.2107705	-2.742273	-3.0749062
WTP Estimates For Sample Plan Where:	$884	$1,463	-$1,700	$546

At-risk homes bought out (000's)= 1.2				
At-risk homes protected (000's)= 13.2				
At-risk saltmarsh lost (acres)= 262				
At-risk beach lost (miles)= .3				
Approval by Bought-out Homes= 80%				
Fish/Shellfish Population Lost (%)= 5%				
Nuisance Flooding Days of Roads= 22				
At-risk Homes Plan Contribution (%)= 40%				

	Region C			
	MNL	LCM-Class 1	LCM-Class 2	LCM-Weighted Avg.
Utility Value of No Action Status Quo	-1.39439307	-2.77275479	-2.24560271	-2.6198807
WTP Estimates For Sample Plan Where:	$1,096	$3,765	-$673	$2,478
At-risk homes bought out (000's)= .335				
At-risk homes protected (000's)= 3.685				
At-risk saltmarsh lost (acres)= 693				
At-risk beach lost (miles)= .7				
Approval by Bought-out Homes= 80%				
Fish/Shellfish Population Lost (%)= 5%				
Nuisance Flooding Days of Roads= 22				
At-risk Homes Plan Contribution (%)= 40%				

	Region D			
	MNL	LCM-Class 1	LCM-Class 2	LCM-Weighted Avg.
Utility Value of No Action Status Quo	-1.21171935	-2.1718125	-2.66989993	-2.3162579
WTP Estimates For Sample Plan Where:	$847	$3,370	-$665	$2,200
At-risk homes bought out (000's)= .25				
At-risk homes protected (000's)= 2.75				
At-risk saltmarsh lost (acres)= 72				
At-risk beach lost (miles)= .1				
Approval by Bought-out Homes= 80%				
Fish/Shellfish Population Lost (%)= 5%				
Nuisance Flooding Days of Roads= 22				
At-risk Homes Plan Contribution (%)= 40%				

4 Conclusions

The application of LCM allowed us to account for preference heterogeneity in a model with respondents in two preference classes, using respondents' answers to Likert scale questions and their demographic attributes to predict the likelihood an individual will belong to a particular preference class, and how class membership may influence their choices. Though our models were unable to converge using every variable as in the Multinomial Logit models for $C>2$, it produced statistically significant results for interpretation.[11]

We had hypothesized that inland coastal town residents would be willing to pay more for, or otherwise increase political support for coastal resilience action if (a) it does not adversely affect natural assets or ecosystem services; (b) it benefits distressed or lower-income communities; (c) defensive benefits help to minimize damage to homes at-risk of repeated flood or storm damage; (d) coastal residents benefiting from the defensive adaptations bear a larger share of the cost; (e) changes are made voluntarily by owners of at-risk built assets; and (f) willingness to pay is conditional on their geographic location along the Connecticut coastline, and their latent attitudes that are in part affected by that location. A discussion of each of these hypotheses based on the results follows.

4.1 Natural Assets or Ecosystem Services

The attributes used to represent natural assets and ecosystem services (Saltmarsh Loss, Beach Loss, and Fish/Shellfish Population Loss) had mixed effects across models, classes and regions. In the Multinomial Logit model, we find that the loss of saltmarsh and beach are highly significant and have a negative impact on the probability that a respondent would choose a particular plan. The coefficients on these variables are also strongly influenced by a respondent's region. For example, the negative effect is increased on saltmarsh loss and beach loss for respondents living in regions A, B, and D relative to Region C, with Region D having the strongest effect from beach loss, and Region A having the strongest effect from saltmarsh loss.

[11] Interpretation could be subject to omitted variables bias as convergence difficulties prevented analysis of additional variables.

Given that Regions A and D have the two smallest no-action status quo levels for at-risk beach and saltmarsh, we note that an incremental change is larger in those regions than in Regions B and C which have much larger no-action status quo levels for these variables and therefore larger denominators (i.e. a loss of 1 acre is a larger percent of total at-risk acres in Regions A and D than in Regions B and C).

For Fish and Shellfish Population loss on the other hand, the coefficient is negative indicating respondents do not want increased loss of populations, but it is not statistically significant in this model. Under the Multinomial Logit Model, we can reject the null hypothesis that Beaches and Saltmarsh as natural assets do not influence public willingness to pay but are unable to confidently do so for Fish and Shellfish populations.

In our 2-class LCM, we find that respondents in Class 1 (the majority share class at 71%) place significant negative value the "Type 1 SQ- No New Action" and the "Type 2 Alternative Specific" choice option that would revert natural assets to the no-action status quo levels. Additionally, Class 1 significantly and negatively values Saltmarsh loss, but these respondents do not have significant coefficients on Beach loss or Fish and Shellfish Population loss. There is strong statistical significance on regional interactions with these variables, indicating that region does in fact affect preference related to these attributes in the LCM, particularly for Region A Saltmarsh Loss, and Region B beach loss.

Like the Multinomial Logit Model, the 2-class latent class model does not indicate significant value on Fish and Shellfish Population loss in Class 1. However, given that most of our sample would be in this class and would significantly negatively value the other natural asset attributes, (Saltmarsh and Beach loss), and choice question types with the greatest amount of environmental detriment, we can also reject the null for Environmental Assets using the 2-class latent class model. We conclude that respondents' support increases when natural assets are not negatively impacted.

4.2 Benefits to Distressed of Low-Income Communities

While our Multinomial Logit model (Table 9) does not test for it, our PCA determined that there exists an explanatory component related to altruism, suggesting some respondents are willing to provide public assistance to at least some of the coastal at-risk homes. This Principal Component 4- Altruism, was shown to be statistically significant in the class membership model for Class 1 in our 2-class LCM, having a positive effect that they would be in Class 1. Within Class 1, coefficients on At-risk Homes Protected and At-risk Homes Bought Out both were positive and highly significant. Regional effects made these effects smaller in Regions A and B, but never to negative values.[12] However, the class membership model does tell us that respondents who are male, non-white, and have low-education levels are less likely to be in Class 1. Nevertheless, recalling that male, non-white, and low-education indicators do not apply to the majority of respondents (Table 5) , we can interpret this as the majority of respondents care about what happens to people living in at-risk homes, regardless of income level, and such respondents receive greater utility from plans that provide aid to those households. We therefore reject the null hypothesis that plans that would provide support to distressed or low-income communities would give respondents no additional value to this public support feature, so that our results suggest most respondent are willing to pay for a coastal management plan that helps lower-income communities.[13]

[12] Coincidentally, these regions have the highest and lowest population-weighted average median household incomes. For more information see Appendix G.
[13] Though less than 2% of respondents to our survey lived within a flood zone, future research could consider how wealth and proximity to a flood zone affect support for plans that defend residents of different income levels.

4.3 Minimizing Damage to At-risk Homes from Repeated Storms or Floods

Building off the conclusion related to Benefits to Distressed of Low-Income Communities, our Multinomial Logit Model also found statistically significant, positive coefficients related to the protection or purchasing of at-risk homes. Region C as the reference region has a positive WTP for avoiding future damage to at-risk homes, particularly when they are bought out and removed to allow for saltmarsh expansion. Regions A and B adjust that WTP downwards but also have positive and statistically significant WTP. Region D does not show coefficients significantly different from reference Region C. We therefore can reject the null hypothesis that minimizing damage from repeated severe storms and floods on at-risk homes has no effect on respondent's willingness to pay a positive amount for a coastal management plan.

4.4 At-risk Households Contributions to the Cost of Plans that Directly Benefit Them

The focus of this study was on inland residents of coastal towns and what their willingness to pay for coastal management plans might be, but in reality, these are not the only residents contributing to the plan. The inclusion of the attribute "At-risk Homes Plan Contribution" in our choice questions allowed us to vary the contribution levels by at-risk homes and test how that affected survey respondents' WTP. The Multinomial Logit model produced a positive and statistically significant coefficient on contribution levels indicating that when at-risk homes were responsible for more of a plan's costs, respondent WTP increased.[14]

Likewise, in the 2-class LCM, "At-risk Homes Plan Contribution" had statistically significant, positive coefficients for Class 1. Class 2 on the other hand, does not have a significant coefficient on "At-risk Homes Plan Contribution", but they also have negative willingness to pay for the protection or purchase of at-risk homes in general, indicating a preference to not do

[14] We did not test this by region though this could be something interesting to look at in future studies.

anything about at-risk homes in general, regardless of whether the at-risk homes are going to pay more for it. In general, we can reject the null hypothesis that when at-risk homes contribute more to a plan that provides defensive benefits to them, it does not affect inland residents' willingness to pay for that plan.

4.5 Voluntary Changes made by Owners of At-risk Homes

A strategy for erosion management and flood control described to respondents in the instructional video was buying-out coastal homes and removing them to allow for saltmarsh expansion. The attribute "Approval by Bought-out Homes" was used to establish plans that would result in "X% of bought-out homes willingly accepted the offer and sold". In other words, they would not necessarily be "forced" out of their properties but would be appropriately compensated to voluntarily sell their home for it to be removed and allow for increased saltmarsh expansion.

The Multinomial Logit model produced a positive coefficient on this model that was statistically significant at the more than 10% level which does not allow us to reject the null at the 5%. However, respondents that fell into Class 1 in the 2-class LCM do have a positive and statistically significant value at the 1% level on the proportion of bought-out homes accept the offer. Under the 2-class model, we can conclude that when a respondent falls into Class 1, the null can be rejected. We also note that approximately 71% of our respondents are likely to be members of Class 1.

4.6 Effects of Regional Variation on Willingness to Pay

By building regional variation into the no-action status quo levels of our survey design, and sending each region their own adjusted survey versions, we can test how variation in these no-action status quo levels affected respondent willingness to pay.

The Multinomial Logit model finds that the interaction of regional dummies on the variables that change from region to region (“At-risk homes bought out”, “At-risk homes protected”, “At-risk saltmarsh lost”, and “At-risk beach lost”) are significantly different than the Region C reference region (Table 10). Instances where there is low significance can be interpreted as having values that are not statistically different from those in Region C. In ten of the 12 regional interaction variables, the coefficients are statistically different from those in Region C at the 10% level. More narrowly, eight of the 12 regional interaction variable coefficients are statistically different than those in Region C at the 5% level.

In the 2-class LCM, 11 of the 12 regional interaction variables are statistically significant at the 10% level, and 10 at the 5% level in Class 1. In Class 2, this ratio is somewhat lower with seven out of 12 region interaction coefficients being statistically significant at the 10% level, and four out 12 at the 5% level. The LCM tells us that for most of our survey sample, regional variability has statistically significant effects on respondent willingness to pay.

We also had hypothesized that respondent’s class would be partially conditional on which region they lived in. The Class 1 membership model coefficients on region are not statistically significant for Regions A or D, and are only weakly significant at the 10% level for Region B.

Thus, for our final hypotheses, we can reject the null that willingness to pay is not conditional on respondent’s geographic location along the Connecticut coastline, but fail to reject that their latent class membership is not conditional on region at the 5% level.

5 Discussion and Future Considerations

The topics of sustainability and coastal management in the context of SLR is only increasing in policy discussions today. The effects of Hurricanes Sandy and Irene jumpstarted policies, such as the Connecticut Coastal Management Act (2012), increased focus on creating coastal adaptation and mitigation plans that are more sustainable, but part of that sustainability is considering the distribution of the costs and benefits different plans can offer to coastal residents.

The conclusions of this study allow us to take a closer look at the preferences and values of Connecticut's coastline residents and the features and outcomes of coastal management plans that benefit them the most. Additionally, providing refined analysis on the regional level can be particularly useful to policy makers as it can allow them to adapt plans that maximize public support in their jurisdiction. This is particularly the case when policy-makers already know or can research the existing sentiment levels (i.e. Principal Component scores) of citizens in their jurisdictions.

However, while this study produced a significant amount of data previously uncollected related to the preferences and perceptions of inland residents of coastal Connecticut towns there are opportunities to improve. Reflection on the design, implementation and analysis processes used for this study uncover several areas of modification or improvement should this study be replicated in the future.

5.1 Survey Pre-Testing

Qualitative pre-testing in the form of focus groups is a critical step in ensuring that a survey design is credible and consequential for respondents. While we did hold one meeting with town planning and zoning managers in Clinton, CT, future attempts to research the preferences of coastal management should probably find resources to enable more extensive incorporation of the knowledge of these professionals in order to improve the realism of the proposed plans and ensure that they closely align with what may actually be proposed. As a CE study, our questions were primarily focused on understanding incremental changes in each attribute, we do not feel that greater discussion with planning and zoning professionals would have affected our results greatly, but it could allow for testing more realistic plans as an alternative choice question type.

Additionally, employing outreach and marketing strategies to procure more diverse focus group participants should be considered. Focus groups with at least 10 participants of various ages, ethnicities, genders and backgrounds can help researchers to refine how respondents perceive the information presented in the choice questions prior to publishing the survey.

5.2 Survey Design

Our survey's choice questions included attributes that were determined to be relevant based on previous related studies (Johnston, Makriyannis, & Whelchel, 2018), focus group pre-testing, and meetings with our research team. However, there are many other natural and built asset attributes that could have been influential but were not included in order to minimize complexity but still capture values related to the natural environment and the built environment. Some examples could include impacts on birds or other coastal animals, impacts on open space and public access to the coast, water quality, influence on tax revenue when bought-out homes are removed, or quantities of low versus high income at-risk households.

Additionally, our survey intended to focus on inland coastal residents by buffering out any possible responses from households within 100 yards of coastal water. However, we do not analyze how preferences change conditional on respondent proximity to water. Using geocoding software to identify each respondent's distance to coastal water could be considered in future research.

5.3 Survey Implementation

The method we used to gain participation, and the method of survey implementation was necessary to reduce costs. Its simple logic that printing and mailing multiple rounds of one-page letters or postcards inviting our sample to participate in an online survey is much less expensive than would be printing and mailing multiple rounds of multi-page, color surveys. However, asking respondents to take additional steps to access the survey (i.e. keeping the letter, having access to a computer and the internet, ensuring the weblink and verification ID's are correctly typed) than they would need to just take a mailed-survey may have affected our response rate. In order to keep costs low but simplify the participation process, it may be useful to consider using some of the printing and mailing budget on purchasing respondent email addresses from a marketing firm as the primary source of contact. If this is attempted, it should be tested against a control group of the standard "letter-to-web" format, or the traditional mailed-survey.

5.4 Data Analysis

Preferably, we wanted an LCM with multiple classes determined by information criteria. As the model would not converge with more than two classes, a future iteration of this study should increase observations in the data set by gathering more survey responses. Larger sample sizes improve the ability of modeling tools to identify the correct number of classes represented in a set of responses, and help ensure significant parameter recovery (Wurpts & Geiser, 2014).

However, with the existing data gathered by this survey, there are also other hypotheses that were not tested but could be. For example, we included a set of Likert Scale Questions related to a respondent's perception of their town's characteristics (e.g. size, population, public involvement in policy decisions, education, etc.) (see the sample survey in Appendix H, Section 5). Given a researcher has quantifiable data on the actual levels of these characteristics as they are in reality, testing could compare how perceptions versus reality affects a respondents WTP. This could also help respondents compare how respondents would choose if their perceptions of reality were as accurate as possible.

References

Connecticut Public Act, C. C. (2012). An Act Concerning the Coastal Management Act and Shorline Flood and Erosion Control Strucutres.

Arrow, K., Solow, R., Portney, P. R., Leamer, E. E., Radner, R., & Schuman, H. (1993). *Report of the NOAA Panel on Contingent Valuation.* National Oceanic and Atmospheric Administration.

Bauer, D. M., Cyr, N. E., & Swallow, S. K. (2004). Public Preferences for Compensatory Mitigation of Salt Marsh Losses: a Contingent Choice of Alternatives. *Conservation Biology*, 401-411.

Boxall, P., & Adamowicz, W. L. (2002). Understanding Heterogeneous Prefernces in Randum Utility Models: a Latent Class Approach. *Environmental Resource Economics*, 421-446.

Boxall, P., Adamowicz, W., & Moon, A. (2009). Complexity in choice experiments: choice of the status quo qlternative and implications for welfare measurement. *The Australian Journal of Agricultural and Resource Economics*, 503-519.

Breffle, W. S., Morey, E. R., & Thacher, J. A. (2011). A Joint Latent-Class Model: Combining Likert-scale Preference Statements with Choice Data to Harvest Preference Heterogeneity. *Environmental Resource Economics*, 83-110.

Cameron, T., DeShazo, J., & Johnson, E. H. (2009). Scenario adjustment in stated preference reserach. *Journal of Choice Modelling*, 9-43.

Carson, R. T. (2000). Contingent Valuation: A User's Guide. *Environmental Science & Technology*, 1413-1418.

Carson, R. T., & Groves, T. (2007). Incentive and informational properties of preference quesitons. *Environmental Resource Economics*, 181-210.

Connecticut Department of Energy and Environmental Protection. (2014). *2014 Connecticut Natural Hazards Mitigation Plan Update.* Hartford: State of Connecticut.

Connecticut Economic Resource Center. (2018, April). *Connecticut Town Profiles.* Retrieved from profiles.ctdata.org: http://profiles.ctdata.org/

Connecticut Sea Grant. (2018, October 23). *Science Serving the Connecticut Coast: Connecticut Sea Grant Strategic Plan 2018-2021.* Retrieved from seagrant.uconn.edu: https://seagrant.uconn.edu/wp-content/uploads/sites/1985/2017/04/CTSG-strategic-plan-2018-2021.pdf

DeShazo, J., & Fermo, G. (2002). Designing Choice Sets for Stated Preference Methods: The EFfects of Complexity on Choice Consistency. *Journal of Environmental Economics and Management*, 123-243.

Evans, K. S., Noblet, C. L., Fox, E., Bell, K. P., & Kaminski, A. (2017). Public acceptance of coastal zone management efforts: The role of citizen preferencces in the allocation of funds. *Agricultural and Resource Economics REview*, 268-295.

Federal Emergency Management Agency. (2018, October 23). *Data Visualization: Summary of Disaster Declarations and Grants*. Retrieved from www.fema.gov: https://www.fema.gov/data-visualization-summary-disaster-declarations-and-grants

Hanley, N., MacMillan, D., Wright, R. E., Bullock, C., Simpson, I., Parsisson, D., & Crabtree, B. (1998). Contingent Valuation Versus Choice Experiments: Estimating the Benefits of Environmentally Sensitive Areas in Scotland. *Journal of Agricultural Economics*, 1-15.

Herriges, J., Kling, C., Liu, C.-C., & Tobias, J. (2010). What are the consequences of consequentiality? *Journal of Environmental Economics and Management*, 67-81.

Hoyos, D., Mariel, P., & Hess, S. (2015). Incorporating environmental attitudes in discrete choice models: An exploration of the utility of the awareness of consequences scale. *Science of the Total Environment*, 1100-1111.

Intergovernmental Panel on Climate Change. (2018). *Global Warming of 1.5°C.* Switzerland: IPCC.

Jackson, J. E. (1991). *A User's Guide to Principal Components.* New York: John Wiley & Sons, Inc.

Johnston, R. J., & Abdulrahman, A. S. (2017). Systematic non-response in discrete choice experiments: Implacations for the valuation of climate risk reductions. *Journal of Environmental Economics and Policy*, 2-22.

Johnston, R. J., Boyle, K. J., Adamowicz, W., Bennett, J., Brouwer, R., Cameron, T. A., . . . Vossler, C. A. (2017). Contemporary Guidance for stated Preference Studies. *Journal of the Association of Environmental and Resource Economics*, 319-405.

Johnston, R. J., Magnusson, G., Mazzotta, M., & Opaluch, J. J. (2002). Combining Economic and Ecological Indicators to Prioritize Salt Marsh Restoration Actions. *American Journal of Agricultural Ecnomics*, 1362-1370.

Johnston, R. J., Makriyannis, C., & Whelchel, A. W. (2018). Using Ecosystem Service Values to Evaluate Tradeoffs in Coastal Hazard Adaptation. *Coastal Management*, 259-277.

Johnston, R. J., Swallow, S. K., & Weaver, T. F. (1999). Estimating willingness to pay and resource tradeoffs with different payment mechanisms: An evaluation of a funding guarantee for watershed management. *Journal of Environmental Economics and Management*, 97-120.

Johnston, R. J., Weaver, T. F., Smith, L. A., & Swallow, S. K. (1995, February). Contingnet Valuation Focus Groups: Insights from Ethnographic Interview Techniques. *Agricurltural and Resource Economics Review*, pp. 56-69.

Johnston, R. J., Whelchel, A. W., Makriyannis, C., & Yao, L. (2015). *Adapting to Coastl Storms and Flooding: Report(s) on a 2014 Survey of Old Saybrook and Waterford.* Worcester, MA: George Perkins Marsh Institute, Clark University, and the Nature Conservancy, Connecticut Chapter.

Kafle, A., Swallow, S. K., & Smith, E. C. (2015). Does Public Funding Affect Preferred Tradeoffs and Crowd-in or Crowd-out Willingness to Pay? A Watershed Management Case. *Environmental Resource Economics*, 471-495.

Kim, Y., Kling, C. L., & Zhao, J. (2015). Understanding Behavioral Explanations of the WTP-WTA Divergence Through a Neoclassical Lens: Implications for Environmental Policy. *Annual Review of Resource Economics*, 169-187.

Kriesel, W., Landry, C. E., & Keeler, A. (2005). Coastal Erosion Management from a Community Economics Perspective: The Feasibility and Efficiency of User Fees. *Journal of Agricultural and Applied Economics*, 451-461.

Kriesel, W., Landry, C. E., & Keeler, A. (2005). Coastal Erosion Management from a Community Economics Perspective: the Feasiblity and EFficiency of User Fees. *Jouranl of Agricutlural and Applied Economics*, 451-461.

Krutilla, J. V. (1967). Conservation Reconsidered. *The American Economic Review*, 777-786.

Kuhfield, W. F. (2005). Marketing research methhods in SAS. In *Experimental design, choice, conjoint, and graphical techniques.* Cary, North Carolina: SAS Institute.

Long Island Sound Study. (2018). *LISS Ecosystem Targets and Supporting Indicators.* Retrieved from longislandsoundstudy.net: http://longislandsoundstudy.net/ecosystem-target-indicators/coastal-habtiat-extent/

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka, *Frontiers in Economics* (pp. 105-42). New York: Academy Press.

McGonagle, M. P., & Swallow, S. K. (2005). Open Space and Public Access: A Contingent Choice Application to Coastal Preservation. *Land Economices*, 477-495.

McGonagle, M. P., & Swallow, S. K. (2006). Public Funding of Environmental Amenities: Contingent Choices Using New Taxes or Existing Revenues for Coastal Land Conservation. *Land Economics*, 56-67.

Millennium Ecosystem Assessment . (2005). *Ecosystems and Human Well-Being: Synthesis.* Washington, DC: ISLAND PRESS.

Mitchell, R., & Carson, R. (1989). *Using Surveys to Value Public Goods: The Contingent Valuation Model.* Washington, D.C.: Resources for the Future.

Morrison, M. D., Blamey, R. K., & Bennett, J. W. (2000). Minimising payment vehicle bias in contingen valuation studies. *Environmental and Resource Economics*, 407-422.

National Ocean Service. (2018, June 25). *What is high tide flooding?* Retrieved from oceanservice.noaa.gov: https://oceanservice.noaa.gov/facts/nuisance-flooding.html

National Oceanic and Atmospheric Administration. (2014). *Sea Level Rise and Nuisance Flood Frequency Changes around the United States.* Silver Spring, Maryland: Department of Commerce.

New England Interstate Water Pollution Control Commission. (2015). *Application of SLAMM to Coastal Connecticut Final Report.* Warren Pinnacle Consulting, Inc.

Nixon, R. (2012). Seeking Revenue, Postal Service Plans to Deliver More Junk Mail. *The New York Times*.

NOAA. (2014). *Insights into Coastal Managment Needs: Results from the NOAA Coastal Services Center and Office of Ocean and Coastal Resource Management Customer Survey*. Lexington: Eastern Research Group, Inc.

NOAA. (2019, March 24). *What is a living shoreline?* . Retrieved from oceanservice.noaa.gov: https://oceanservice.noaa.gov/facts/living-shoreline.html

O'Donnell, J. (2018). *Sea Level Rise in Connecticut.* Department of Marine Sciences and Connecticut Institute for Resilience and Climate Adaptation .

Pohjola, M. V., & Tuomisto, J. T. (2011). Openness in participation, assessment, and policy making upon issues of environment and environmental health: a review of literature and recent project results. *Environmental Health*, 58-70.

Purdy, K. G., & Decker, D. J. (1989). Applying Wildlife Values Information in Management: The Wildlife Attitudes and Values Scale. *The Wildlife Society Bulletin*, 493-500.

Schlacher, T. A., Dugan, J., Schoeman, D. S., Lastra, M., Jones, A., Scapini, F., . . . Defeo, O. (2007). Sandy beaches at the brink. *Diversity and Distributions*, 556-560.

Smyth, J. D., Dillman, D. A., Christian, L. M., & O'Neill, A. c. (2010). Using the Internet to Survey Small Towns and Communities: Limitations and the Possibilities in the Early 21st Century . *American Behavioral Scientist*, 1423-1448.

Swait, J. (2007). Advanced choice models. In B. Kanninen, *Valuing environmental amenities using stated choice studies* (pp. 229-293). Dordrecht.

Swallow, S. K. (1996). Economic Issues in Ecosystem Management: An Introduction and Overview. *Agricultural and Resource Economics Review*, 83-100.

Taylor, L. O., Morrison, M. D., & Boyle, K. J. (2010). Exchange Rules and the Incntive compatibility of Choice Experiments. *Environmental Resource Economics*, 197-220.

The World Bank. (2018, October 29). *Zoning and Land Use Planning*. Retrieved from urban-regeneration.worldbank.org: https://urban-regeneration.worldbank.org/node/39

Train, K. E., & McFadden, D. L. (1987). Consumer Attitudes and Voluntary Rate Schedules for Public Utilities. *The Review of Economics and Statistics*, 383-391.

U.S. Census Bureau. (2019, March 22). *American Fact Finder*. Retrieved from factfinder.census.gov: https://factfinder.census.gov/faces/nav/jsf/pages/community_facts.xhtml

U.S. Climate Resilience Toolkit. (2017, October 6). *Storm Surge*. Retrieved from toolkit.climate.gov: https://toolkit.climate.gov/topics/coastal/storm-surge

U.S. Environmental Protection Agency. (2018, October 23). *What is Green Infrastructure?* Retrieved from www.epa.gov: https://www.epa.gov/green-infrastructure/what-green-infrastructure

Vossler, C. A., & Watson, S. B. (2013). Understanding the consequences of consequentiality: Tesing the validity of stated preferences in the field. *Journal of Economic Behavior and Organization*, 137-147.

Vossler, C. A., Doyon, M., & Rondeau, D. (2012). Truth in Consequentiality: Theory and Field Evidence on Discrete Choice Experiments. *American Economic Journal: Microeconomics* , 145-171.

Wainger, L. A., King, D. M., Mack, R. N., Price, E. W., & Maslin, T. (2009). Can the concept of ecosystem services be practically applied to improve natural resource management decisiosns? . *Ecological Economics*, 978-987.

Wambuguh, O. (2011). Junk mail in residential homes in the United States: Insights from a sub-urban home in California. *Resources, Conservation, and Recycling*, 782-784.

Washburn, E., Smythe, T., Wiley, P., Feurt, C., & Ryan, T. (2018). Applying Ecosystem Services to the Practice of Coastal Management: an Overview. *Coastal Management*.

Weinstein, M. P., Baird, R. C., Conover, D. O., Gross, m., Keurlartz, J., Loomis, D. K., . . . van der Windt, H. J. (2007, February). Managing coastal resources in the 21st century. *Frontiers in Ecology and the Environment*, pp. 43-48.

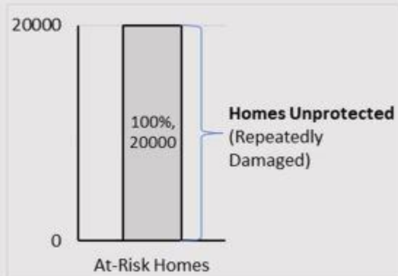
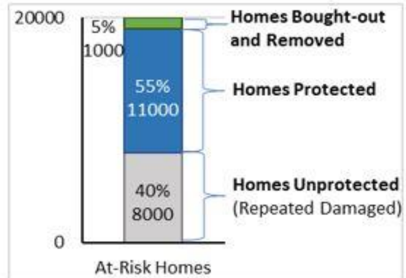
Whitehead, J. C., Blomquist, G. C., Ready, R. C., & Huang, J.-C. (1998). Construct Validity of Dichotomous and Polychotomous Choice Contingent Valuation Questions. *Environmental and Resource Economics*, 107-116.

Wurpts, I. C., & Geiser, C. (2014). Is adding more indicators to latent class analysis beneficial or detrimental? Results of a Monte-Carlo Study. *Frontiers in Psychology*.

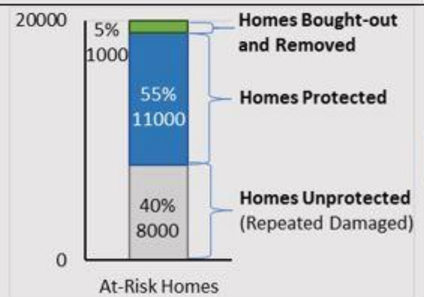
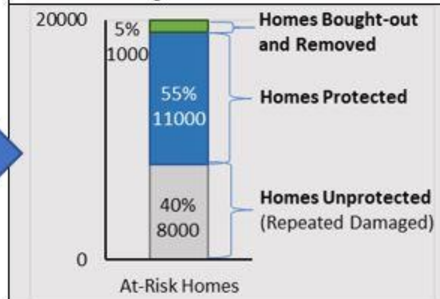
Zachry, B. C., Booth, W. J., Rhome, J. R., & Sharon, T. M. (2015). A Ntional View of Storm Surge Risk and Inundation. *Weather, Climate, and Society*, 109-117.

Appendix A- Choice Question Samples

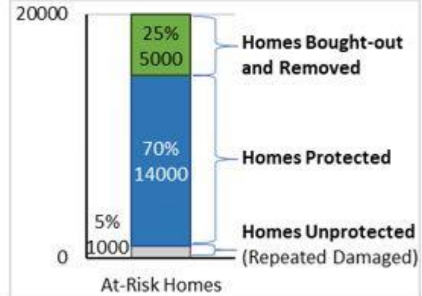
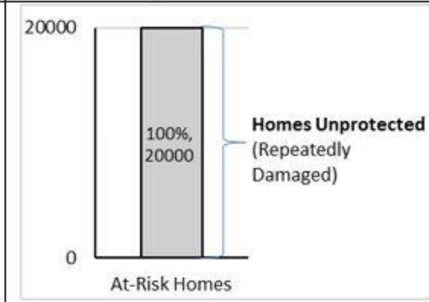
A.1 Sample "Type 1" Choice Question

Impacts by 2055	No New Action	Proposed Plan A	Proposed Plan B
Impacts on homes currently at-risk for repeated flood damage			
Bought-out homeowners' voluntary offer-acceptance	**No homes are bought out**; leading to results above.	**80%** of all offers made are accepted; leading to results above.	**40%** of all offers made are accepted; leading to results above.
Impacts on Salt Marsh by 2055	Decrease of **72 acres (11%)** by 2055, **0 acres** are maintained or replaced	Decrease of **33 acres (5%)** by 2055, **39 acres** are maintained or replaced	Decrease of **33 acres (5%)** by 2055, **39 acres** are maintained or replaced
Impacts on Beaches by 2055	Decrease by **1 mile (4%)** from erosion or conversion to salt marsh by 2055	Decrease by **0.2 miles (1%)** from erosion or conversion to salt marsh by 2055	Decrease by **0.7 miles (3%)** from erosion or conversion to salt marsh by 2055
Impacts on Local Fish/Shellfish by 2055	Population decreases by **15%** (habitat loss) by 2055	Population decreases by **5%** (habitat loss) by 2055	Population decreases by **5%** (habitat loss) by 2055
Impacts on Major, Local Roads by 2055	Up to **25** nuisance flooding days/year by 2055	Up to **22** nuisance flooding days/year by 2055	Up to **7** nuisance flooding days/year by 2055
At-Risk Homes Share of Plan Cost	**Does not apply** (but public continues to pay federal disaster relief)	**40%** (public sector contributes 60% for defenses)	**40%** (public sector contributes 60% for defenses)
Additional tax change for you	You pay $**0**/year in new property taxes (cost covered by existing tax payments).	You pay an additional **$200**/ year in property taxes for 10 years.	You pay an additional **$1200**/ year in property taxes for 10 years.

A.2 Sample “Type 2” Choice Question

Impacts by 2055	Current Plan		Adjusted Plan A	Adjusted Plan B
Impacts on homes currently at-risk for repeated flood damage		Same		
Bought-out homeowners’ voluntary offer-acceptance	**80%** of all offers made are accepted; leading to results above.	Same	**80%** of all offers made are accepted; leading to results above.	**80%** of all offers made are accepted; leading to results above.
Impacts on Salt Marsh by 2055	Decrease of **7 acres (1%)** by 2055, **68 acres** are maintained or replaced		Decrease by **72 acres (11%)** by 2055, **0 acres** are maintained or replaced	Decrease of **66 acres (10%)** by 2055, **6 acres** are maintained or replaced
Impacts on Beaches by 2055	Decrease by **0.7 miles (3%)** from erosion or conversion to salt marsh by 2055		Decrease by **1.0 mile (4%)** from erosion or conversion to salt marsh by 2055	Decrease by **0.7 miles (3%)** from erosion or conversion to salt marsh by 2055
Impacts on Local Fish/Shellfish by 2055	Population decreases by **5%** (habitat loss) by 2055		Population decreases by **15%** (habitat loss) by 2055	Population decreases by **5%** (habitat loss) by 2055
Impacts on Major, Local Roads by 2055	Up to **22** nuisance flooding days/year by 2055		Up to **25** nuisance flooding days/year by 2055	Up to **7** nuisance flooding days/year by 2055
At-Risk Homes Share of Plan Cost	**20%** (public sector contributes 80% for defenses)	Same	**20%** (public sector contributes 80% for defenses)	**20%** (public sector contributes 80% for defenses)
Additional tax change for you	**$0** in new taxes per year (cost covered by existing tax payments)		You receive a **$200**/ year tax reduction for 10 years	You pay an additional **$500**/ year in property taxes for 10 years

A.3 Sample Type 3 Choice Question

Impacts by 2055	Current Plan		Adjusted Plan A	Adjusted Plan B
Impacts on homes currently at-risk for repeated flood damage				
Bought-out homeowners' voluntary offer-acceptance	**80%** of all offers made are accepted; leading to results above.		**40%** of all offers made are accepted; leading to results above.	No offers are made and no new protections; leading to results above.
Impacts on Salt Marsh by 2055	Decrease of **7 acres (1%)** by 2055, **65 acres** are maintained or replaced	Same	Decrease of **7 acres (1%)** by 2055, **65 acres** are maintained or replaced	Decrease of **7 acres (1%)** by 2055, **65 acres** are maintained or replaced
Impacts on Beaches by 2055	Decrease by **0.7 miles (3%)** from erosion or conversion to salt marsh by 2055	Same	Decrease by **0.7 miles (3%)** from erosion or conversion to salt marsh by 2055	Decrease by **0.7 miles (3%)** from erosion or conversion to salt marsh by 2055
Impacts on Local Fish/Shellfish by 2055	Population decreases by **0%** (habitat loss) by 2055	Same	Population decreases by **0%** (habitat loss) by 2055	Population decreases by **0%** (habitat loss) by 2055
Impacts on Major, Local Roads by 2055	Up to **15** nuisance flooding days/year by 2055	Same	Up to **15** nuisance flooding days/year by 2055	Up to **15** nuisance flooding days/year by 2055
At-Risk Homes Share of Plan Cost	**60%** (public sector contributes 40% for defenses)		**20%** (public sector contributes 80% for defenses)	**0%** (but public continues to pay federal disaster relief)
Additional tax change for you	**$0** in new taxes per year (cost covered by existing tax payments)		You pay an additional **$750**/ year in property taxes for 10 years	You receive a **$750**/ year tax reduction for 10 years

Appendix B- Likert Scale Questions used in Principal Component Analysis

Question/ Statement	Scale	Variable Name
Level of concern today:		
Impacts from coastal flooding on human-built assets like houses and buildings.	1-7	FloodDamageBldgToday
Impacts from coastal flooding on local ecosystems and wildlife.	1-7	FloodDamageEcoToday
Changes in the frequency of severe storms in your town.	1-7	StormFrequencyToday
Changes in local, coastal high tide levels in your town.	1-7	HighTideChangesToday
Impacts on coastal natural assets (like beaches and salt marsh) resulting from man-made flooding adaptations (like sea walls).	1-7	HumanImpactsEcoToday
Level of concern in 30 years:		
Impacts from coastal flooding on human-built assets like houses and buildings.	1-7	FloodDamageBldg30yrs
Impacts from coastal flooding on local ecosystems and wildlife.	1-7	FloodDamageEco30yrs
Changes in the frequency of severe storms in your town	1-7	StormFrequency30yrs
Changes in local, coastal high tide levels in your town.		HighTideChanges30yrs
Impacts on coastal natural assets (like beaches and salt marsh) resulting from man-made flooding adaptations (like sea walls).	1-7	HumanImpactsEco30yrs
Personal Importance (MCAVs)		
Development of private coastal lands is managed so that everyone can still have some way to access the local coast.	1-7	PrvtMgmtPublicAccess
Development of coastal land is managed to protect wildlife habitat.	1-7	PrvtDevelopPublicAccess
Coastal habitats are maintained in their natural state.	1-7	CoastalHabitatMaintained

Coastal land owners can develop their property how they choose.	1-7	PropertyDevelopRights
Public officials seriously consider all residents’ opinions about the coast.	1-7	PublicOpinion
Tourists have access to the shore.	1-7	TouristAccess
Wildlife protection programs do not block public access to the coast.	1-7	WildlifePublicAccess
Action to sustain human-built assets like homes and businesses also allows replacement of natural assets like beaches and saltmarsh.	1-7	ReplaceNaturalAssets
Access to environmentally sensitive coastal land is restricted as needed to protect wildlife.	1-7	RestrictedAccessWildlife
The local economy benefits from products or services related to coastal development, recreation and tourism.	1-7	LocalCoastalEconomy
Everyone who benefits from the coast in some way contributes to its protection.	1-7	ContributeCoastProtection
There is public access to the coast.	1-7	PublicCoastalAccess
I can visit, observe or photograph the coast.	1-7	RespondentCoastalAcccess
I have access to private coastal land.	1-7	RespondentPrivateAccess
Personal Importance on Natural or Recreational Resources		
Public beach(es)	1-7	PublicBeachesImportance
Private beach(es)	1-7	PrivateBeachesImportance
Endangered species	1-7	EndSpeciesImportance
Fishing access	1-7	FishingAccessImportance
Coastal businesses	1-7	CoastalBusinessImportance
Local “coastal town charm”	1-7	LocalCharmImportance
Dunes	1-7	DunesImportance

Fish & wildlife habitat	1-7	WildlifeHabitatImportance
Tidal marshes	1-7	TidalMarshImportance
Motor boats access	1-7	BoatAccessImportance
Canoe/Kayaking	1-7	KayakAccessImportance
Waterside roadway	1-7	CoastalRoadImportance
Areas of undeveloped coastline	1-7	UndevelCoastImportance
Historically significant coastal sites	1-7	HistoricSiteImportance
How Deserving of Public Aid At-risk Homes are; by Income		
Very low-income households (4 people living on less than $45,000/year)	1-7	PublicAidVeryLowIncome
Low-income households (4 people living on $45,000- $68,000/year)	1-7	PublicAidLowIncome
Middle class households (4 people living on $69,000-$127,000/year)	1-7	PublicAidMiddleClass
Upper-middle class households (4 people living on $128,000-$183,000/year)	1-7	PublicAidUpperMidClass
Wealthy households (4 people living on more than $183,000/year)	1-7	PublicAidWealthy

Appendix C- Multinomial Logit Variable Table

Variable Name	Description
At-risk homes bought out (000's)	Quantity of at-risk homes bought out and removed (in thousands)
At-risk homes protected (000's)	Quantity of at-risk homes protected (in thousands)
At-risk saltmarsh lost (acres)	Proportion of at-risk homes that are bought out and removed that voluntarily accept the purchase offer (%)
At-risk beach lost (miles)	Saltmarsh acres lost
Approval by Bought-out Homes (%)	Beach miles lost
Fish/Shellfish Population Lost (%)	Fish/shellfish population lost
Nuisance Flooding Days of Roads	Nuisance flooding days
At-risk Homes Plan Contribution (%)	Proportion of the plan cost that at-risk homes contribute (%)
Cost Attributes	
Change to household property tax ($1,000s)	Increase (or decrease) to household property tax ($)
Question Type Status Quo Dummies	
Type 1 SQ- No New Action	Dummy for “Type 1” Status quo
Type 2 SQ- Built Asset Focused	Dummy for “Type 2” Status quo
Type 3 SQ- Natural Asset Focused	Dummy for “Type 3” Status quo
Type 2 Alt. Specific- Natural Assets Reset to No New Action	Dummy for “Type 2” Alternative that returns some attributes to baseline
Type 3 Alt. Specific- Built Assets Reset to No New Action	Dummy for “Type 3” Alternative that returns some attributes to baseline
Region A Interactions	
At-risk homes bought out (000's) * RegionA	Quantity of at-risk homes bought out and removed (in thousands) * Region A dummy
At-risk homes protected (000's)*RegionA	Quantity of at-risk homes protected (in thousands) * Region A dummy
At-risk saltmarsh lost (acres)*RegionA	Saltmarsh acres lost * Region A Dummy
At-risk beach lost (miles)*RegionA	Beach miles lost* Region A Dummy

Variable Name	Description
Region B Interactions	
At-risk homes bought out (000's)*RegionB	Quantity of at-risk homes bought out and removed (in thousands) * Region B dummy
At-risk homes protected (000's)*RegionB	Quantity of at-risk homes protected (in thousands) * Region B dummy
At-risk saltmarsh lost (acres)*RegionB	Saltmarsh acres lost * Region B Dummy
At-risk beach lost (miles)*RegionB	Beach miles lost* Region B Dummy
Region D Interactions	
At-risk homes bought out (000's)*RegionD	Quantity of at-risk homes bought out and removed (in thousands) * Region D dummy
At-risk homes protected (000's)*RegionD	Quantity of at-risk homes protected (in thousands) * Region D dummy
At-risk saltmarsh lost (acres)*RegionD	Saltmarsh acres lost * Region D Dummy
At-risk beach lost (miles)*RegionD	Beach miles lost* Region D Dummy
Status Quo-Demographic Interactions	
Type 1 SQ*LMI	"Type 1" Status quo* Dummy for "Low-to-moderate income"=1
Type 2 SQ*LMI	"Type 2" Status quo* Dummy for "Low-to-moderate income"=1
Type 3 SQ*LMI	"Type 3" Status quo* Dummy for "Low-to-moderate income"=1
Type 2 Alt. Specific*LMI	"Type 2" Alternative Specific * Dummy for Low-to-moderate income"=1
Type 3 Alt. Specific*LMI	"Type 3" Alternative Specific * Dummy for Low-to-moderate income"=1
Type 1 SQ*Non-White	"Type 1" Status quo* Dummy for "nonwhite ethnicity" =1
Type 2 SQ*Non-White	"Type 2" Status quo* Dummy for "nonwhite ethnicity" =1
Type 3 SQ*Non-White	"Type 3" Status quo* Dummy for "nonwhite ethnicity" =1
Type 2 Alt. Specific*Non-White	"Type 2" Alternative Specific * Dummy for "nonwhite ethnicity"=1

Variable Name	Description
Type 3 Alt. Specific*Non-White	“Type 3” Alternative Specific * Dummy for “nonwhite ethnicity”=1
Type 1 SQ*Male	“Type 1” Status quo* Dummy for Male=1
Type 2 SQ*Male	“Type 2” Status quo* Dummy for Male=1
Type 3 SQ*Male	“Type 3” Status quo* Dummy for Male=1
Type 2 Alt. Specific*Male	“Type 2” Alternative Specific * Dummy for Male=1
Type 3 Alt. Specific*Male	“Type 3” Alternative Specific * Dummy for Male=1”
Type 1 SQ*Low Education	“Type 1” Status quo* Dummy for “no higher education” =1
Type 2 SQ*Low Education	“Type 2” Status quo* Dummy for “no higher education” =1
Type 3 SQ*Low Education	“Type 3” Status quo* Dummy for “no higher education” =1
Type 2 Alt. Specific* Low Education	“Type 2” Alternative Specific * Dummy for “no higher education”=1
Type 3 Alt. Specific* Low Education	“Type 3” Alternative Specific * Dummy for “no higher education”=1

Appendix D- Informational Video

Policy makers are trying to design a coastal flooding and storm surge adaptation plan in your region. As you take this survey, think of your town and other nearby towns. For each question, we'll ask you to consider the costs and outcomes of three different plans for coastal flooding adaptation. Each plan is considered to be feasible. Your choices will help us to develop a picture of what kind of plan Connecticut residents would prefer when it is simply too expensive to include everything and making a choice involves picking the best options people are willing to support.

There will be three sets of questions. One will compare two alternative, potential plans of action against a plan called **No New Action. No New Action** will remain the same in each of the questions and will present the regional outcomes by 2055 if no new action is taken; essentially, "business as usual". This plan will have either no new cost to you or a tax reduction. Tax reductions occur when local governments forego a proposed action plan and are able to reallocate funds back to the taxpayers in your region. The two alternative, proposed plans, called Plan A and Plan B, will produce sets of outcomes in your region by 2055 that are different than those resulting from **No New Action**. These plans will either have no impact on your current property taxes, or come at a new tax to you, added to your property taxes.

The other two sets of questions will ask you to consider a case where your region has chosen an action plan, called Current Plan. You will be asked to choose whether to stick with that current plan, or to choose an "Adjusted Plan" which will only change certain components of the current plan. These adjusted plans come at either a new tax or a tax rebate to you, while the Current Plan would have no effect on your taxes and would be funded through reallocation of existing tax revenue, grants, or donations.

Each plan uses combinations of different strategies to achieve their outcomes, though the plans will not explicitly state the combinations. These strategies include wetland and salt marsh expansion, restoration, or maintenance; adaptation measures like elevating structures, engineered flood-proofing, zoning restrictions, or removing or relocating houses away from the coast; and coastal armoring through seawalls, bulkheads, and revetments.

These measures can interact with each other. Wetlands expansion helps to slow land erosion and decrease the reach of flooding. It also provides critical habitat for fish and wildlife, which can also support food, recreation, tourism, local business, and an aesthetic quality unique to coastal communities.

However, creating more space for wetlands sometimes requires the removal or relocation of buildings. This can be voluntary if property owners feel that they are fairly compensated. In many circumstances, property owners have the right to try to defend their property from flood damage. But coastal armoring which tends to protect homes and buildings, can block expansion of wetlands and cause erosion of existing wetlands and beaches.

The plans in each question specify outcomes in eight (8) categories that will result from implementing those plans. What is key to remember while reviewing these outcomes is that No

New Action demonstrates the unmitigated impacts of sea level rise and predicted storm surges by 2055, while the alternative plans state how they will alter those same outcomes.

The plans also specify cost you would incur. This amount will be an annual charge added to your property taxes as a payment mechanism. **We do understand that the taxpayers of Connecticut already feel overtaxed, but this study cannot resolve that issue.** So, for the context of this survey, please consider this a charge that is guaranteed to fund only the associated project or plan.

Please understand that your listed cost in the form of a tax **does not** represent the plan's total cost, but your personal contribution to the plan. This cost could be different from what others in your region would pay. Plans also likely would be funded in part by federal or private grants, but we do not state what that funding amount might be.

Additionally, some plans may actually provide you with a tax rebate. This means that the plans overall cost would be less expensive than originally planned.

We thank you in advance for your time. Please review each plan's outcomes costs and vote for the plan you are most willing to pay for.

Sea Grant Survey Instructions- Link to Video on Youtube

Appendix E- Sample Survey Participation Invitation Mailings

E.1. Business Letter

Recipient Name
Recipient Address
Address Line 2

MAILING DATE

Dear Prefix/ First/ Last,

The State of Connecticut takes pride in its coastline's beauty, history, and resources. Yet maintaining that into the future may require adaptation plans in the face of increasing flooding and storms. Some towns already have a plan in place, but developing one is not always straightforward. These plans can be designed to defend buildings and other man-made coastal resources, protect, or expand natural resources, slow flooding and erosion, or a combination of these things.

Your mailing address has been randomly selected from the voter registration list to receive this survey. In this survey, we ask for your help to improve our understanding of coastal Connecticut residents' views on coastal flooding and its effects on Connecticut's communities. As we cannot afford to survey everyone, your response is important so that households with preferences like yours can be represented. Please be assured that your identity will be kept strictly confidential and **your responses will never be associated with your name or mailing address in any reports.**

The survey is an online format and will ask you a series of questions to understand your current perspective. Your answers will provide data that can be used by towns and the State of Connecticut to evaluate which options their residents would be willing to support as towns adapt to coastal flooding and storms. Many people complete the survey in 30 minutes or less. Your prompt response will help us avoid sending reminders.

You can access and complete the survey by typing the "bit.ly" link into your web browser. This is a unique link, shortened for your convenience, which will direct you to a Qualtrics survey page. Enter your verification code to begin the survey. **The survey displays best on a desktop or laptop.** If you have difficulty accessing your survey, please email Julia.dumaine@uconn.edu with your name and town and we will provide you with a clickable link.

Bit.ly link
TOWNCODE-SURVEYCODE-RANDCODE
"0" = zero "O" = the letter "O"
"1" = one "l" = lowercase letter "L"

Thank you for your time and thoughtful participation,

Stephen Swallow, Ph.D
stephen.swallow@uconn.edu
Principal Investigator

Julia Dumaine, Gradate Research Assistant
Julia.dumaine@uconn.edu
(860)202-1232

If you have any concerns regarding your privacy rights, you may call University of Connecticut Institutional Review Board (IRB) 860-486-8802 and reference project number X16-074.

E.2 Post Card

Return Address

PLEASE
PLACE
STAMP
HERE

Mailing Address Line 1
Mailing Address Line 2
Mailing Address Line 3
Mailing Address Line 4
Mailing Address Line 5

To avoid receiving additional mailings, your survey response is requested.

UCONN
UNIVERSITY OF CONNECTICUT

Be sure to capitalize!

Your web link:
uconnsurvey.com/D1321

Your 10-digit access code:
Town-survey-rand

If you have any concerns regarding your privacy rights, you may call University of Connecticut Institutional Review Board 860-486-8802 and reference project number X16-074.

If you cannot access or use your survey link, please email Julia.Dumaine@uconn.edu with your name, town and 10-digit code, or call (860)202-1232.

Connecticut policy makers want to hear <u>your</u> opinion on using state and town funds for adapting Connecticut's coast-line to increasing storms and flooding.

Ensure that your voice is heard by taking our survey online. By completing it online, you'll help our graduate researchers avoid the high cost of printing and mailing paper surveys, which will be sent after the online survey closes.

The "PRINTLINK" link will take you to a Qualtrics survey specific to your town. Please type that link exactly into your internet browser and enter your 10-digit code at the prompt.

UCONN
UNIVERSITY OF CONNECTICUT

Sea Grant
Connecticut

CIRCA
Connecticut Institute for Resilience and Climate Adaptation

Appendix F- Principal Component Analysis Eigenvalues

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	13.6077	9.07066	0.3165	0.3165
Comp2	4.53703	0.208326	0.1055	0.422
Comp3	4.3287	2.10499	0.1007	0.5226
Comp4	2.22371	0.204146	0.0517	0.5744
Comp5	2.01956	0.701158	0.047	0.6213
Comp6	1.3184	0.288131	0.0307	0.652
Comp7	1.03027	0.0405246	0.024	0.6759
Comp8	0.989749	0.0925008	0.023	0.699
Comp9	0.897248	0.080248	0.0209	0.7198
Comp10	0.817	0.0609055	0.019	0.7388
Comp11	0.756095	0.0209193	0.0176	0.7564
Comp12	0.735175	0.0839236	0.0171	0.7735
Comp13	0.651252	0.015651	0.0151	0.7886
Comp14	0.635601	0.0437184	0.0148	0.8034
Comp15	0.591882	0.0132364	0.0138	0.8172
Comp16	0.578646	0.0295668	0.0135	0.8307
Comp17	0.549079	0.0284236	0.0128	0.8434
Comp18	0.520656	0.00600362	0.0121	0.8555
Comp19	0.514652	0.0271375	0.012	0.8675
Comp20	0.487514	0.00432203	0.0113	0.8788
Comp21	0.483192	0.0191869	0.0112	0.8901
Comp22	0.464006	0.0160219	0.0108	0.9009
Comp23	0.447984	0.0372486	0.0104	0.9113
Comp24	0.410735	0.0254573	0.0096	0.9208
Comp25	0.385278	0.010392	0.009	0.9298
Comp26	0.374886	0.0291083	0.0087	0.9385
Comp27	0.345778	0.0244456	0.008	0.9466
Comp28	0.321332	0.0105244	0.0075	0.954
Comp29	0.310808	0.0562848	0.0072	0.9613
Comp30	0.254523	0.0292101	0.0059	0.9672
Comp31	0.225313	0.0115354	0.0052	0.9724
Comp32	0.213777	0.0364866	0.005	0.9774
Comp33	0.177291	0.0218724	0.0041	0.9815
Comp34	0.155418	0.0209872	0.0036	0.9851
Comp35	0.134431	0.0238023	0.0031	0.9882
Comp36	0.110629	0.0210108	0.0026	0.9908
Comp37	0.0896178	0.00746646	0.0021	0.9929
Comp38	0.0821514	0.0182558	0.0019	0.9948
Comp39	0.0638956	0.0118365	0.0015	0.9963
Comp40	0.0520591	0.00378754	0.0012	0.9975
Comp41	0.0482715	0.00705625	0.0011	0.9986
Comp42	0.0412153	0.0237139	0.001	0.9996
Comp43	0.0175014	.	0.0004	1

Appendix G- Demographic Statistics (Actuals)

Town	Population	Housing Units	Median Age	Pop. Weighted Average Median Age	Median HH Income	Pop. Weighted Average Median HH Income	White	Non-white	Bachelors or More	Less than Bachelors	Total Educated Pop.
Region A	**387,902**	**139,474**	**41**	**39**	**$132,220**	**$109,332**	**65%**	**35%**	**70%**	**30%**	**204,926**
Greenwich	62,418	22,113	43		$134,223		46,707	15,711	27,893	6,411	34,304
Stamford	127,410	47,708	36		$81,634		63,256	64,154	42,319	23,863	66,182
Darien	21,519	6,618	39		$208,125		19,179	2,340	10,262	1,526	11,788
Norwalk	87,930	33,184	39		$80,896		46,731	41,199	25,716	18,394	44,110
Westport	27,511	9,696	45		$166,307		23,648	3,863	13,946	2,442	16,388
Fairfield	61,114	20,155	41		$122,135		51,987	9,127	23,980	8,174	32,154
Region B	**467,144**	**180,972**	**39**	**36**	**$57,741**	**$51,248**	**43%**	**57%**	**42%**	**58%**	**206,284**
Bridgeport	147,022	57,658	33		$43,137		31,942	115,080	16,728	36,209	52,937
Stratford	52,300	20,540	44		$69,336		33,970	18,330	12,692	15,354	28,046
Milford	53,430	21,549	44		$81,844		45,212	8,218	16,190	14,443	30,633
West Haven	54,972	19,961	36		$50,831		28,864	26,108	7,897	15,826	23,723
New Haven	130,405	50,024	31		$38,126		40,164	90,241	27,810	27,973	55,783
East Haven	29,015	11,240	43		$63,173		22,898	6,117	4,904	10,258	15,162
Region C	**98,861**	**39,942**	**49**	**48**	**$86,912**	**$86,991**	**90%**	**10%**	**63%**	**37%**	**57,555**
Branford	28,084	12,264	47		$71,619		25,096	2,988	8,995	7,143	16,138
Guilford	22,382	8,553	48		$102,199		20,377	2,005	9,704	3,686	13,390
Madison	18,247	6,791	48		$105,673		16,902	1,345	8,148	2,530	10,678
Clinton	13,072	5,294	46		$74,022		11,795	1,277	3,516	3,641	7,157
Westbrook	6,902	2,839	51		$92,721		6,380	522	2,277	2,036	4,313
Old Saybrook	10,174	4,201	51		$75,237		8,851	1,323	3,403	2,476	5,879
Region D	**131,258**	**52,863**	**43**	**40**	**$71,730**	**$66,808**	**74%**	**26%**	**52%**	**48%**	**66,214**
Old Lyme	7,539	3,191	51		$87,971		7,090	449	3,012	1,504	4,516
East Lyme	18,929	7,330	47		$85,872		15,408	3,521	6,431	4,317	10,748
Waterford	19,332	7,813	48		$78,832		16,332	3,000	5,246	5,763	11,009
New London	27,218	10,600	31		$35,357		12,865	14,353	3,782	6,024	9,806
Groton	39,763	16,051	34		$64,074		28,759	11,004	9,707	9,384	19,091
Stonington	18,477	7,878	48		$78,274		16,829	1,648	6,413	4,631	11,044

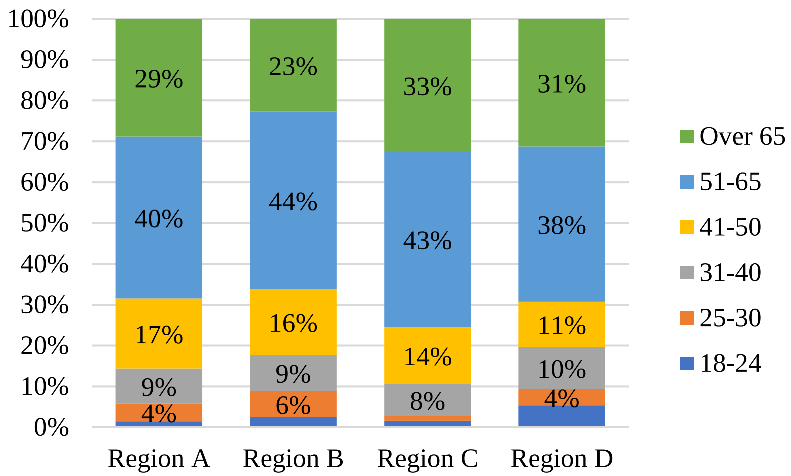
Appendix H- Reported Demographic Statistics

H.1 Mean and Mode

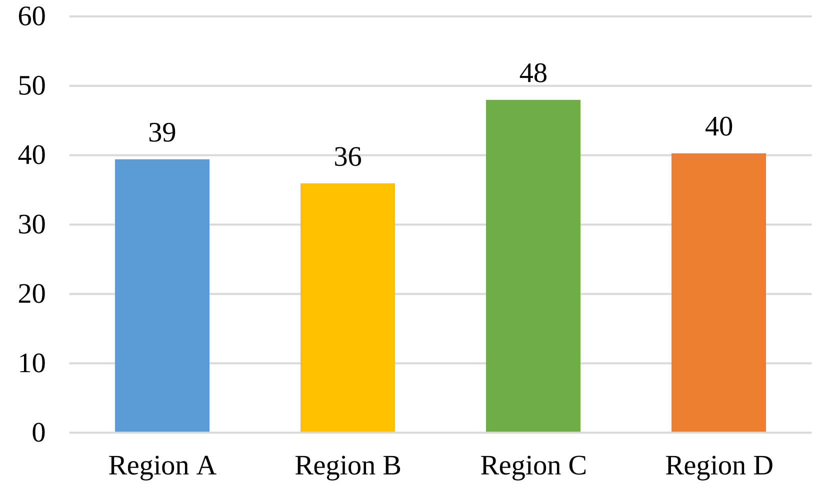
Table 5: Average Respondent Reported Socioeconomic and Demographic Statistics

Variable	Description	Mode	Mean	Std. Dev.	Min	Max
Age	1=18-24, 2=25-30, 3=31-40, 4=41-50, 5=51-65, 6=65+	71% over 50	4.76	1.23	1	6
Income	1=$0-$50k, 2=$50,001-$82k, 3=$82,001-$115k, 4=$115,001-$149k, 5=$149,001-$165k, 6=$165k+, 0=Not willing to say	41% over $115,000	3.06	2.01	1	7
Education	1= Some high school or less, 2=high school graduate, 3=Some college no degree, 4=Trade school, 5=Associate's, 6=Bachelor's, 7=Master's, 8= Doctorate	75% Bachelors or more	5.96	1.80	1	8
Ethnicity	1= Asian, 2=Black/African American, 3=Hispanic/Latino, 4=Other 5=Pacific Islander, 6=White	90% White	5.67	1.08	1	6
Coastal Distance	1=Less than 100ft, 2=0.1-0.25mi, 3=0.25-0.5mi, 4=0.5-1mi, 5=More than 1mi	52% More than 1 mile	3.97	1.20	1	5
Gender	1=Male	52% Female	0.48	0.50	0	1
FEMA Flood Zone	1= No, 2=Not Sure, 3=Yes	74% No	1.37	0.663	1	3

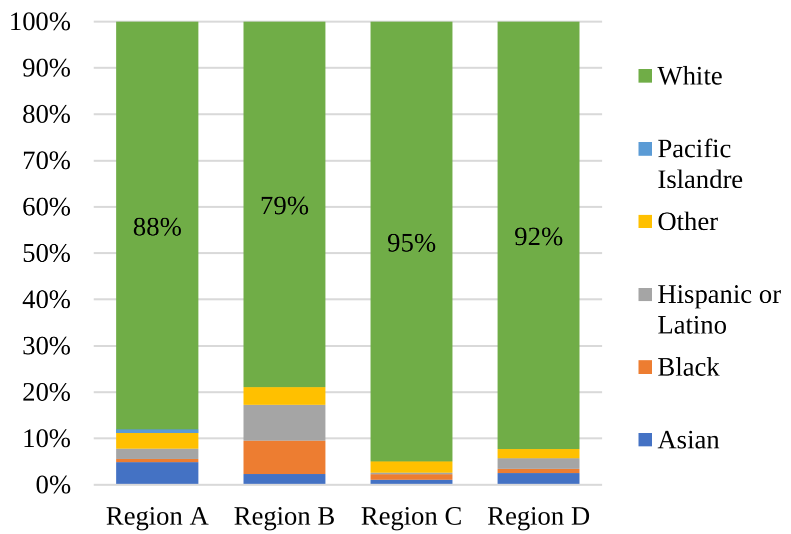
H.2- Graphic Comparison of Actual Demographic Statistics and Respondent-Reported Statistics



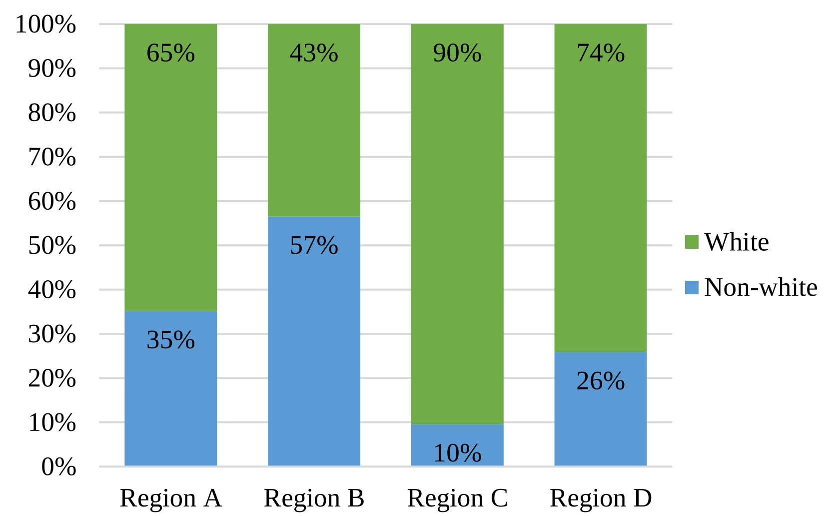
Survey Respondent-Reported Age Range



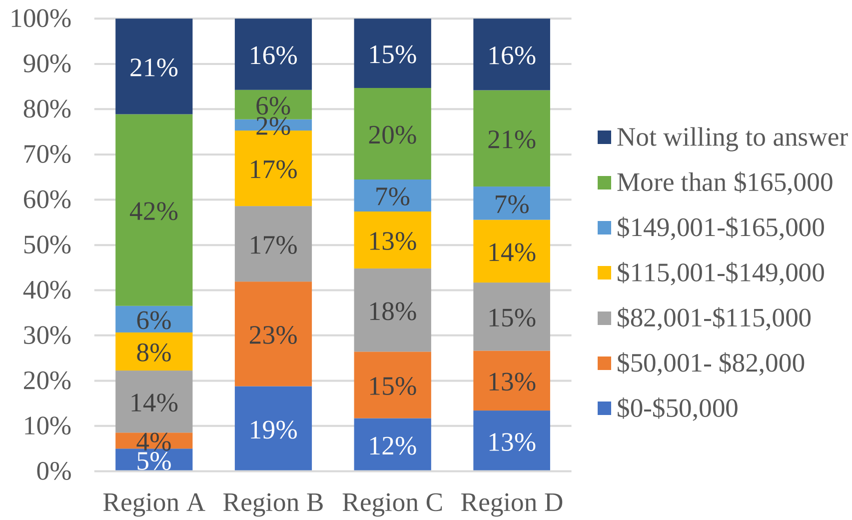
Pop. Weighted Average Actual Median Age



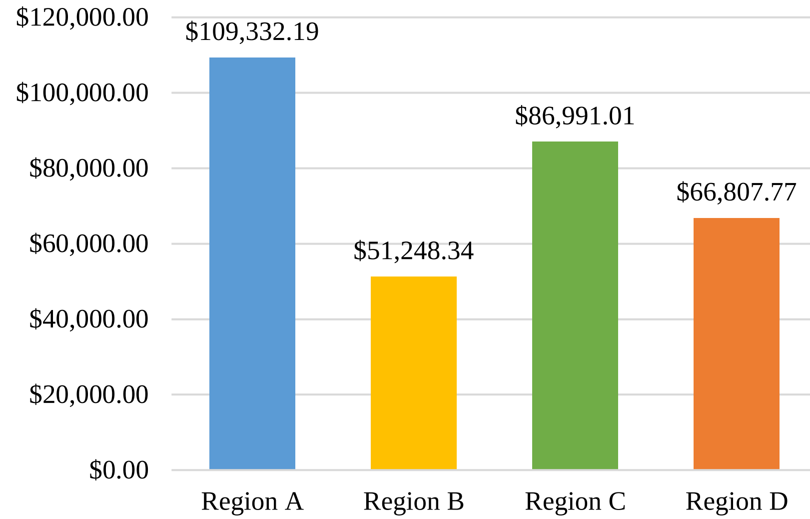
Survey Respondent-Reported Ethnicity



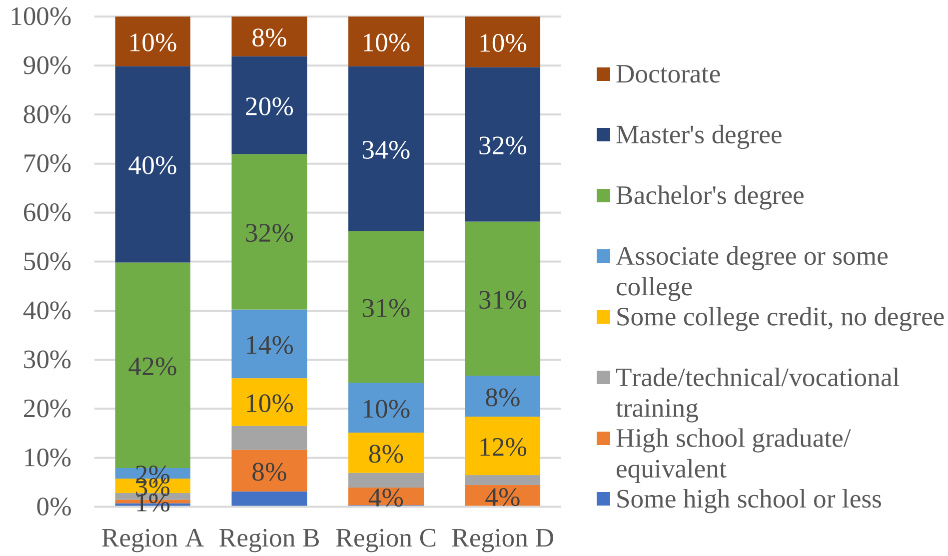
Actual Population Ethnicity



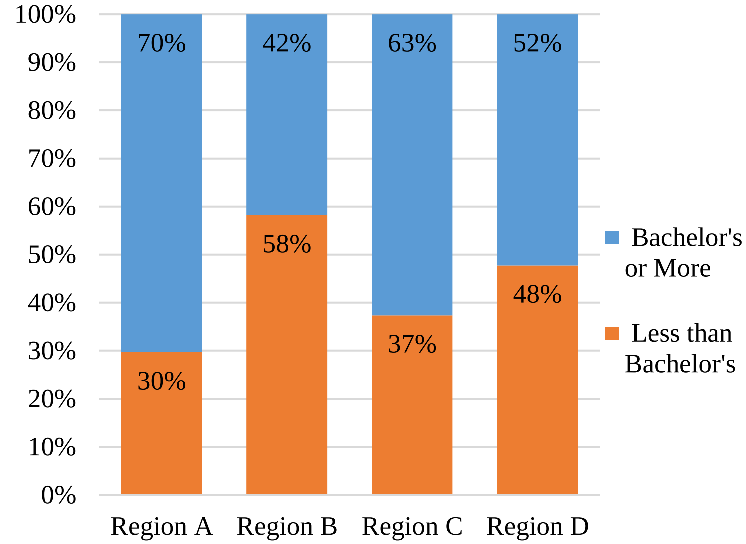
Survey Respondent-Reported Household Income



Pop. Weighted Actual Average Median Household Income



Survey Respondent-Reported Education Level



Actual Adult Education Level