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Non-participation and Heterogeneity in Stated: A Double Hurdle Latent Class Approach for Climate Change Adaptation Plans and Ecosystem Services

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Abstract

We introduce a double hurdle latent class approach to model choice experiments, where serial non-participants and clustered preference patterns are present. The proposed approach is applied to a recent stated preference study in which the residents of the Eastern Shore of Virginia answer choice questions about alternative coastal climate change adaptation plans. While the double hurdle latent class model avoids self-contradictory assumptions, estimates and tests show that, compared with an unrestricted latent class model, it achieves a significantly better statistical fit and maintains the capability to link the heterogeneity of participants' preferences to their attributes. Moreover, the double hurdle latent class model also provides important implications in how to conduct welfare analysis based on different behavioral patterns of different groups, which leads to nontrivial changes in welfare measures. The empirical results highlight that certain ecosystem services may increase the willingness to pay for coastal climate change adaptation plans.

Keywords Built assets · Choice experiment · Double hurdle model · Mixture model · Natural assets · Serial non-participation · Valuation · Resilience · Adaptation · Sea-level rise

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1 Introduction

Climate change is a controversial topic in the U.S. (Shapiro 2016), and a related stated preference study may, therefore, involve people who are reluctant to make choices implying their acceptance of climate change science and related policies. Such individuals are likely to signal that maintaining the status quo is their preference always, yet others may have different motives for choosing the status quo through a series of alternative management choices. Distinguishing these groups, who may initially appear observationally equivalent, can significantly improve the discrete choice analysis. We propose a double hurdle latent class (DHLC) model, which gives more careful consideration of how different groups answer choice questions differently. More importantly, this paper explores how the DHLC may improve welfare analyses in stated preference studies.

Since the introduction of random coefficient discrete choice models (Train 1995, 1998; Revelt and Train 1998; Chen and Cosslett 1998) and latent class discrete choice models (McCutcheon 1987; Boxall and Adamowicz 2002), many environmental valuation studies have modeled distributions of heterogeneous preferences among individuals, rather than relying exclusively on categorical or dummy-variable interactions (e.g., Swallow et al. 1994). This literature also exhibits a growing awareness of situations in which respondents appear never to consider tradeoffs in option attributes, such as by repeatedly choosing one alternative option, often the status quo, within a series of choice occasions. As suggested in previous studies, these non-participants are not playing the trade-off game that the participants play and represent a fundamentally different behavioral process (e.g., von Haefen et al. 2005). This awareness inspires studies to explicitly model these individuals as serial non-participants.

Primary studies of serial non-participation include the use of double hurdle random parameter models (von Haefen et al. 2005) or latent class models (Burton and Rigby 2009) to address the phenomenon that some respondents may not be evaluating tradeoffs and choices within a utility maximization framework. However, though current approaches function properly in discerning the serial non-participants and participant heterogeneities, they have certain disadvantages. Given the prior knowledge of individuals (e.g., demographics) required in a double hurdle approach, a simple random coefficient approach in the second hurdle (e.g., von Haefen et al. 2005) cannot effectively utilize this prior information in addressing the heterogeneity among participants, while a latent class approach can. However, the latent class models depict the serial non-participants as one latent class where the choice equation is based on random utility modeling, which is contradictory to the basic definition of non-participation and potentially leads to biases in choice modeling and welfare analyses.

To describe the multi-level heterogeneity among survey respondents, we propose a DHLC model, in which the first hurdle deals with the serial non-participation issue, while the second hurdle, with a latent class structure, addresses the heterogeneous preferences among participants.[1] Burton and Rigby (2009) formally compared the latent class (LC) approach (i.e., latent class models) and double hurdle approach (i.e., double hurdle random coefficient models) in dealing with non-participation, and argue that the advantage of an

[1] Note that "the respondents" represent all the individuals who responded, while "the participants" refer to all the respondents who are not non-participants, that is, who are making choices in a manner that indicates that they evaluated tradeoffs and in a manner that (presumably) reflects their preferences in the choice occasions.

LC approach is that the non-participation need not be defined in advance. Our paper offers a comparison focused only on the difference made by the hurdle structure,[2] and provides four reasons that the LC model is less preferred in modeling serial non-participants. First, modeling serial non-participants with LC models involves inconsistent underlying assumptions: the fundamental nature of non-participants suggests they are not evaluating tradeoffs among attributes and act fundamentally differently compared to the participants, while the LC modeling assumes they can properly fit into a random utility structure like the participants. Second, though it seems LC models do not adopt any prior definition of non-participation, they implicitly adopt a definition of non-participation when interpreting one latent class as non-participants, which is problematic since the “non-participation class” does not necessarily only include non-participants—it also includes people who actually play the participants’ game but end up deciding to choose the status quo across many questions. Third, the unrestricted LC models perform significantly worse than the DHLC models in fitting the data generation process, while the highly restricted LC models[3] (i.e., with only a status quo indicator in the choice equation of the “non-participation class”), performing similarly to DHLC models, contradicts the claimed advantage of not needing a prior definition. Finally, the aforementioned inconsistent assumptions and modeling in LC models lead to different estimates compared to the DHLC models, with the most noticeable differences lying in the WTP estimates. For example, relative to DHLC models, LC models consistently lead to higher sample WTP estimates—usually by a margin of more than $100 or 50% as shown in Table 9).

At least within the scope of our data, we argue the proposed combination of a double hurdle structure with the latent class approach generally performs better, relative to LC models, in fitting the data generation process as well as inferring the segmentation, preferences, and willingness to pay (WTP) of respondents. While we recognize LC models as good tools to detect or explore non-participation patterns, we recommend stated preference studies with serial non-participants draw welfare measures based on DHLC models.

We pursue the DHLC approach with data from a recently finished stated preference (SP) survey, through which the residents of the Eastern Shore of Virginia, USA, answer discrete choice questions about alternative climate change adaptation plans. This study specifically compared conventionally engineered seawalls and “green” nature-based protections identified as living shoreline (LS hereafter). In focus groups to develop the Eastern Shore Survey (ESS), clusters of Eastern Shore residents were observed to hold qualitatively similar opinions toward the local environment and coastal projects, which serves as a practical motivation for the latent class approach in the analysis of survey data. In addition to the discrete choice questions, the

[2] Burton and Rigby (2009) compared a restricted latent class model with a double hurdle random coefficient model, in which the differences are sourced from the hurdle structure as well as the differences between the latent class modeling and random coefficient modeling. We compare latent class models with double hurdle latent class models, where the double hurdle structure is the only major source of differences.

[3] One may argue that in the restricted LC models, the “non-participation” class is not modeled to be evaluating the trade-offs among different attributes since there’s only one attribute in the choice equation. Although that seems to be true, it is still not consistent with the fundamental modeling problem. First, no matter what parameters are included or what specifications are adopted in the multinomial logit structure, that structure is generated from the random utility theory and the status quo parameter is part of the random utility model. Second, the assumed non-participation behavior reflects a decision to adopt a particular choice or response process based on a categorical variable, and generally, the non-participants’ decision is to choose the option with the status quo variable being 1. Since there’s only one status quo option in each choice occasion, no uncertainty nor random utility is involved. Thus, a multinomial logit structure conflicts with the theoretical conceptualization of the non-participant’s response process.

ESS also collected information on respondents' demographics and attitudes toward environmental protection and ecosystem services. Considering the important role of spatial attributes in forming environmental preferences and supporting related benefit transfer studies (Bateman et al. 2006; Brouwer et al. 2010; Johnston and Ramachandran 2014; Johnston et al. 2015), we also collect Geographic Information System (GIS) data and include it in the probability analysis to identify class membership.

Information criteria and Vuong tests (Vuong 1989) show that the DHLC model is significantly preferred in terms of statistical fit to the baseline unrestricted LC model but not to an LC model with its non-participation choice equation restricted by a prior definition. The estimation results suggest that the DHLC model maintains the latent class structure of the baseline LC model. The LC model with four segments suggests that the survey respondents consist of four latent classes: the pro-nature group, the moderate environmentalist group, the economy group, and the non-participant group. The DHLC model separates out the non-participant group with its hurdle analysis and shows three participating classes corresponding to the first three classes in the LC model. Moreover, the welfare analysis shows that, compared with the LC model, the DHLC model produces different choice equation parameters, which results in consistently and considerably lower welfare measures. We further provide conceptual explanations of why these differences come from treating the non-participants as one latent class (in the LC models) and why the DHLC model offers a better understanding of the segmentation, preference, and willingness to pays of respondents.

Further welfare analysis based on the DHLC model provides valuable information regarding preferences for coastal management. First, our analysis shows considerable heterogeneity in Eastern Shore residents' WTP for coastal climate change adaptation plans (coastal plans hereafter): besides the serial non-participants, the class-specific total WTP for a given alternative plan could range from several dollars to several hundred dollars. Second, our results suggest that some ecosystem services bundled with coastal plans are quite important, at least for the residents of Eastern Shore of Virginia. In addition, we find a segment called the pro-nature group, comprised of individuals who have a statistically insignificant response to a plan's monetary cost and have a significantly positive preference for LS, and assume that this pro-nature group can accommodate the costs that the other participating groups are willing to pay. Finally, the analysis of expected sample WTP suggests that the general Eastern Shore population would have a higher proportion of non-participants and hence has a lower projected average WTP than the respondents. In general, the Eastern Shore residents' average willingness to pay for different coastal plans roughly ranges from \$45 to \$170, expressed as tax payments per year for five years.

The rest of this paper is organized as follows. The next section develops the econometric model of the DHLC approach and discusses the specifications. The third Section presents details of the SP survey design and the data, including the choice experiment and supporting questions. The fourth section presents the estimation results and welfare analysis. The fifth section discusses the implications of the results, for both the econometric modeling and climate change adaptation approaches. Finally, we discuss the findings in the last section.

2 Methodology

2.1 Heterogeneity and the Latent Class Model

Latent class (LC) models are well-known discrete choice models for analyzing heterogeneities, particularly offering the advantage of being capable of linking heterogeneous preferences to individual specific attributes. Here, a latent class logit model will be presented as the baseline model. According to the random utility theory and conditional choice modeling (McFadden 1973; Hanemann 1984), the consumer utility of choosing the jth alternative on choice occasion t (or question t in the setting of the ESS) can be represented by the following conditional indirect utility function:

$$V\left(y - C_{jt}, S_{jt}; \beta\right) + \varepsilon_{jt}, \tag{1}$$

where $\boldsymbol{y}$ is normalized income, $\boldsymbol{C}_{jt}$ is the cost for alternative $\boldsymbol{j}$ (additional tax each year for 5 years in the ESS), and $\boldsymbol{S}_{jt}$ is the observable attributes of the alternative option $\boldsymbol{j}$. $\boldsymbol{\beta}$ is a set of parameters which can be fixed or following some distribution across the participants. $\boldsymbol{\varepsilon}_{jt}$ represents all the other determinants unknown by the researcher, and are assumed to be captured by an independently distributed[4] Type-I extreme value random variable with scale factor 1. The likelihood of observing the $\boldsymbol{n}$th individual choosing the $\boldsymbol{j}$th alternative on choice occasion $\boldsymbol{t}$ takes the form of a standard multinomial logit (McFadden 1973):

$$L_{njt} = \frac{e^{V\left(y_n - C_{njt}, S_{njt}; \beta\right)}}{\sum_i^I e^{V\left(y_n - C_{nit}, S_{nit}; \beta\right)}}, \tag{2}$$

where $\boldsymbol{i}, \boldsymbol{j}$ denote the order of the alternative choices under each choice occasion, $\boldsymbol{I}$ represents the number of alternative choices included in a choice occasion. If we assume the same independent preference structure underlies each choice occasion for one individual, the likelihood of observing a series of choices is the product of $\boldsymbol{L}_{njt}$, which can be represented by the following formula:

$$L_n = \prod_t^T \prod_j^J \left(L_{njt}\right)^{1_{njt}}, \tag{3}$$

where 1_{njt} is an indicator function equal to one if individual n chose the jth alternative on choice occasion $\boldsymbol{t}$, and zero otherwise. Thus, for each choice occasion, only the logit probability of the chosen alternative enters the formula.

In the discrete choice experiment (DCE) literature, economists suggest two types of approaches to model the heterogeneity (in β) among subjects: random coefficient approaches (Revelt and Train 1998; Layton and Brown 2000) and latent class approaches (Greene and Hensher 2003; Scarpa and Thiene 2005; Kafle et al. 2015). Although random coefficient multinomial logit modeling can potentially reduce the information loss in the modeling process by assuming subjects follow certain random distributions on certain coefficients, it usually does not explain the sources of these heterogeneities. In contrast,

[4] In the final double hurdle framework, the independence assumption here means that conditional on being a participant, the random (unobserved) part of utilities are independently distributed across different options, different choice occasions, and different individuals.

latent class approaches enable the researchers to show that certain patterns in subject attributes may relate to certain patterns in their choice behaviors. In the ESS focus groups, clusters were observed in Eastern Shore residents' opinions toward the local environment and climate change adaptation projects. To allow for these clustered patterns in residents' environmental preferences, while not complicating the modeling process too much, we employ a latent class logit model without random coefficients.

The following equation system gives the likelihood of observing a series of choices for individual n (L_n) in a standard ***K***-segment latent class logit model (with ***K*** groups each making choices using different representative preference functions):

$$L_{njt|k} = \frac{e^{V\left(y_n - C_{njt}, S_{njt}; \beta_k\right)}}{\sum_i^I e^{V\left(y_n - C_{nit}, S_{nit}; \beta_k\right)}}, \tag{4}$$

$$L_{n|k} = \prod_t^T \prod_j^J \left(L_{njt|k}\right)^{1_{njt}}, \tag{5}$$

$$L_n = \sum_{k=1}^{K} \pi_{nk} L_{n|k}, \tag{6}$$

where $\boldsymbol{\pi}_{nk}$ denotes individual $\boldsymbol{n}$'s probability of falling into class $\boldsymbol{k}$. Assuming the error terms are independently distributed across individuals and segments with Type I extreme value distribution and scale factor $\boldsymbol{\mu}$, we can model the probability of membership in segment $\boldsymbol{k}$ as:

$$\pi_{nk} = \frac{e^{\left(\mu \gamma_k Z_n\right)}}{\sum_{k=1}^{K} e^{\left(\mu \gamma_k Z_n\right)}}, \tag{7}$$

where $\boldsymbol{Z}_n$ denotes individual $\boldsymbol{n}$'s attributes. Therefore, the Log-likelihood function of a standard K-segment latent class logit model is given by:

$$LL(\alpha, \beta) = \sum_n^N \log\left(L_n\right). \tag{8}$$

In addition, we adopt a linear utility specification:

$$V\left(y - C_{jt}, S_{jt}; \beta_k\right) = \beta_{ky}\left(y - C_{jt}\right) + \sum_{m=1}^{M} \beta_{km} S_{jtm}, \tag{9}$$

where $\boldsymbol{m}$ indicates the order of non-monetary attributes in a scenario. This linear-in-income specification allows cancellation of the income terms in the numerator and denominator in Eq. (4), and hence the empirical choice equation would not explicitly include income.[5]

[5] The linear terms involving income, y, are just constant across the utility for each scenario, and therefore do not affect which scenario provides the highest utility; therefore, in a linear utility model, analysts drop income (Hanemann 1984). A negative sign is not explicitly addressed by this simplification, so the estimated parameter on cost should be interpreted accordingly. That is, an estimated negative coefficient on cost suggests a positive marginal utility of income ($\beta_{kC} = -\beta_{ky}$). Moreover, though the choice equations do not include income, income could be included as an indicator in the membership equations.

2.2 Serial Non-participation and the Double Hurdle Latent Class Model

An important observation in the ESS is that more than 20% of our survey respondents always choose the status quo (SQ). This phenomenon is called serial non-participation in previous studies (von Haefen et al. 2005; Burton and Rigsby 2009). Von Haefen et al., (2005) employed a hurdle approach to address the non-participation issue, while Burton and Rigsby (2009) suggested that the latent class model would function similarly regarding detecting serial non-participation. Also, Burton and Rigsby (2009) argued that the latent class model can be used to detect non-participants (i.e., potentially non-participating by choosing status quo in certain questions) other than serial non-participants (i.e., non-participating by choosing status quo across all the questions), and that it's advantage is that it doesn't need a prior definition of non-participants.

However, latent class logit models treat serial non-participants as one latent class and model them using the same utility framework as used for the participants, which offers little attention to fit the fact that these serial non-participants are presumably not actually evaluating tradeoffs implied by choices and stating corresponding preferences. Theoretically, non-participants are defined as a group of respondents who act fundamentally different from participants and provide little information for researchers to infer their values (e.g., marginal WTPs on different attributes). The prior "definition" discussed in this specific setting is actually the process of searching for a reflection for this group of respondents. No matter whether one pre-defines the non-participants (i.e., prior definition can be used to restrict the LC models), the LC models use random utility models to model these respondents who show little utility-evaluating behavior while assuming it is technically and theoretically sound to do so, which is contradictory to the basic meaning of non-participation in a stated preference survey. This inconsistency potentially diminishes the statistical fit and biases the estimates.

Being aware of these advantages and disadvantages, we propose a blended approach that combines the latent class model and the double hurdle model, where the hurdle structure addresses the serial non-participants, while the latent class modeling detects clustered patterns within participants' response set. We call the blended model the double hurdle latent class (DHLC) model.

The double hurdle model requires a specification of the behavior of serial non-participants (SNPs). Here we specify that a serial non-participant always chooses the SQ, which is the commonly accepted prior definition of an SNP. If we model the probability of being an SNP with a probit model, we get:

$$\Pr\{SNP\} = \Phi\left(Z_n'\alpha\right), \tag{10}$$

where we normalize the variance of the residual to 1 and denote the demographics, attitudes, and other individual characteristics with $\boldsymbol{Z}_n$. An implicit assumption here is that the error term in this participation decision and the error terms in the class segmentation model [note that they are already assumed to be independent of each other in Eq. (7)] are independently distributed conditional on observables.

This double hurdle framework does not eliminate the possibility that a utility-maximizing participant may always choose the SQ based on his truthful preferences. Thus, the possibility of observing a subject always choosing the status quo is represented by a summation of two parts:

$$\begin{aligned}\Pr\{All\,SQ\} &= \Pr\{All\,SQ|P\} * (1-\Pr\{SNP\}) + \Pr\{All\,SQ|SNP\}\cdot\Pr\{SNP\}\\ &= L_n * \Phi\left(-Z_n'\alpha\right) + \Phi\left(Z_n'\alpha\right).\end{aligned} \tag{11}$$

$\Pr\{All\,SQ|P\}$ is the probability that a participant (P) always chooses the SQ. This participant is considering tradeoffs in the choice questions, so his utility can be modeled through the discrete choice likelihood function $\boldsymbol{L_n}$ of participants. $\Pr\{All\,SQ|SNP\}$ is the probability that an SNP chooses the SQ, which always equals 1 by the definition of SNP. Similarly, the possibility of observing that a subject does not always choose the SQ is given by:

$$\begin{aligned}\Pr\{Discretechoices\} &= \Pr\{Discretechoices|P\} * (1-\Pr\{SNP\})\\ &= L_n * \Phi\left(-Z_n'\alpha\right).\end{aligned} \tag{12}$$

Thus, the final likelihood function for individual n can be represented as:

$$P_n = L_n * \Phi\left(-Z_n'\alpha\right) + ASQ_n * \Phi\left(Z_n'\alpha\right), \tag{13}$$

where $\boldsymbol{ASQ_n}$ is an indicator that equals one if the individual $\boldsymbol{n}$ always chooses the status quo and equals zero otherwise. From this equation and Eq. (6), we can derive the Log-likelihood function of the DHLC model:

$$LL(\alpha,\beta) = \sum_{n}^{N} \log\left[\Phi\left(-Z_n'\alpha\right) * \sum_{k=1}^{K} \pi_{nk} L_{n|k} + ASQ_n * \Phi\left(Z_n'\alpha\right)\right]. \tag{14}$$

We use the maximum likelihood routine in Stata 14 to estimate the parameters in Eq. (14).

2.3 The Willingness to Pay Measure

An important goal of this study is to estimate Eastern Shore residents' average WTP for an alternative coastal plan. We believe the DHLC model is the most appropriate specification for the welfare analysis since it explicitly addresses the influence of serial non-participants while allowing for observationally equivalent participants. We also present the same welfare measures from the LC model and the widely accepted random coefficient logit model[6] for comparison. Following the approach in Hanemann (1982, 1984), we calculate the class-specific WTP for a given scenario as the compensating surplus associated with the change from the status quo to an alternative coastal plan $\boldsymbol{j}$. This process is expressed by the following equations:

[6] For the econometric approach for a logit model with random parameters, see Revelt and Train (1998), and Layton and Brown (2000). The random coefficient model (without hurdle structure) is presented in Online Appendix F. Also, a latent class model with random coefficients could perform better than both the standard latent class model and the plain random coefficient model, but it would not show the goodness of the double hurdle structure. Hence, we make no additional effort in random coefficient modeling for the latent class model or the double hurdle latent class model, leaving this topic outside the scope of the current paper.

$$V\left(y - WTP_{j|k}, S_j; \beta_k\right) + \varepsilon_{kj} = V\left(y - 0, S_{SQ}; \beta_k\right) + \varepsilon_{k0}; \tag{15}$$

$$E\left(WTP_{j|k}\right) = \left(\sum_{m=1}^{M} \beta_{km} S_{jm} - \beta_{k,SQ}\right) / \beta_{ky}. \tag{16}$$

Since the alternative specific constant is the only parameter specified for the status quo ($\beta_{k,SQ}$), we shall get the class-specific total WTP as specified in Eq. (16), where $\boldsymbol{\beta}_{k,SQ}$ represents the status quo utility level. Also, given our linear indirect utility function in Eq. (9), the marginal willingness to pay for attribute $\boldsymbol{S}_m$ (if evaluated as a continuous variable) can be calculated by: $\boldsymbol{MWTP}_{kjt} = \boldsymbol{\beta}_{km} / \boldsymbol{\beta}_{ky}$.

Moreover, we extend the class-specific WTP to generate an expected WTP measure for the realized sample (i.e., the respondents), which is weighted by individual membership probabilities (Boxall and Adamowicz 2002) and scaled by hurdle probabilities (von Haefen et al. 2005). By further adjustments based on population demographics, we are able to develop an average WTP measure of the standard scenarios for the population (i.e., the Eastern Shore residents).

3 Data and Survey Design

3.1 Survey

Our final survey consisted of four major sections: Section One and Section Two solicit environmental attitudes, section Three contains the DCE questions, and section Four collects demographics. More details about the focus groups and survey questions are provided in Online Appendix A.

Section Three of the survey consisted of eight DCE questions. We presented the eight choice questions in two sets of four. The context for all eight questions was the same: that in 50 years, a certain number of sea-side acres of land in the respondent's county (4500 acres for Northampton, 9500 acres in Accomack) would likely flood as a result of climate change. Each question gave survey respondents the choice of voting to either pay new taxes to help their county fund one of two coastal protection plans (referred to generically as Plan A and Plan B), which would reduce the amount of land that would flood, or vote that the county take "No Action" to mitigate the flooding. Both coastal plans (Plan A and Plan B) consisted of environmental and non-environmental attributes. The exact attributes differed for each set of four choice questions.

The first set of choice questions (Fig. 1(a), Land Type Choice Questions) focused on the types of land that would flood in 50 years. We examined three land types: (i) village, business, and residential land, which comprised 100 of the 4500 acres in Northampton and 1000 of the 9500 acres in Accomack that would flood in 50 years; (ii) cropland and pasture, which comprised 400 acres in Northampton and 1500 acres in Accomack; and (iii) forest and un-farmed fields, which comprised 4000 acres in Northampton and 7000 acres in Accomack. We estimated these flooded acreage values using a simple "bathtub" GIS flood model.[7] The attributes in each Plan included: (1) the total amount of land protected against

[7] Our "bathtub model" was produced by Dr. John H. Porter of the University of Virginia, Department of Environmental Sciences.

flooding, with attribute levels of either low (1500 acres for Northampton and 3000 acres for Accomack) or high (3000 acres for Northampton and 6000 acres for Accomack); (2) the protection method, with attribute levels of conventional coastline protection (seawall, defined as “rock or concrete structures built along the coast, like seawalls, that block waves and redirect water currents”) or alternative coastline protection (living shoreline, defined as a “strategic combination of saltmarsh, sea grass beds, oyster reefs, and rock walls placed along the coast”) for both Northampton and Accomack;[8] (3) the portion (acres) of land, out of the total land protected, made up of (a) village, business, and residential land (with attribute levels of 25, 50, 75, or 100 acres for Northampton and 250, 500, 750, or 1000 acres for Accomack), (b) cropland and pasture (with attribute levels of 0, 100, 250, or 375 acres for Northampton and 0, 500, 1000, or 1400 acres for Accomack), and (c) forest and unfarmed fields (with attribute levels being the difference between the total land protected and the sum of other protected land types); and (4) the cost of the plan in new household taxes paid per year for five years (with attribute levels of \$15, \$30, \$45, \$60, or \$75 for both Counties). The No Action alternative stated that the respondent’s county would not undertake any coastal protection plan.

The second set of choice questions (Fig. 1(b)), the Ecosystem Services Choice Questions, focused on the ecosystem services that could be considered as part of a coastline protection plan. We focused on seven ecosystem services (ES), based on feedback from our focus groups as to which slate would best encompass the most salient ecosystem services for residents. The seven ESs included: habitat and wildlife for future generations (ES 1), removal of excess nutrients from coastal waters (ES 2), stabilization of sediments that cloud coastal waters (ES 3), nature’s protection against destructive waves and salt spray (ES 4), saltmarsh buildup to combat coastal flooding (i.e., saltmarsh accretion) (ES 5), undeveloped landscape views for local quality of life (ES 6), and maintenance of the historic Eastern Shore culture (ES 7). The attributes in each Plan for the Ecosystem Services Choice Questions included the same attributes and levels as for the Land Type Choice Questions, except the land-portion attributes were replaced by three ecosystem services that would be impacted by the coastal protection plan. The way the ecosystem services were considered as part of a Plan was contingent on the protection method (i.e., “enhance or strengthen” for living shoreline while “minimize the negative impacts on” for seawall). No Action alternative indicated that all the acres expected to flood could potentially turn into saltmarsh, which, in turn, might provide any of the ecosystem services listed in Survey Section two.

Using a fractional factorial main effects design,[9] we created eight different surveys for each county (16 different surveys in total) based on four sets of four Land Type Choice Questions and eight sets of four Ecosystem Services Choice Questions for each county (see details in Yue 2017).

We carried out our survey sampling via U.S. Mail. We adopted a six-part survey mailing sequence, based on the Dillman Total Design Survey Method (Dillman 1978, 2011),

[8] We included a preface to Section Three of the survey (see Online Appendix A for more details) in order to define certain terminology and to ensure all survey participants had a common base set of knowledge going into the choice questions.

[9] The design was constructed by Dr. Donald A. Anderson of StatDesign, LLC (Evergreen, CO). See Yue (2017) for details.

sending out surveys (and additional mailings, as appropriate) to 1000 households in each of Northampton and Accomack Counties. The 1000 household addresses in each county are randomly selected from the voter registration lists and other community group lists.[10] We launched the mailing sequence in the fall of 2013.

3.2 Data

Summary statistics for survey responses can be found in Online Appendix B. Overall, we had a 91% survey delivery rate for Northampton and a 90% survey delivery rate for Accomack.[11] The total useful response rate, which takes into account all returned surveys useable in at least one of our data analyses, was 32% in Northampton and 34% in Accomack.[12] In total, there were 293 usable surveys for Northampton and 302 useable surveys for Accomack. Among 4796 choice questions that could be answered by these survey respondents, 229 are skipped and treated as being answered the default option (i.e., status quo).

From a demographic's perspective, our survey sample represents a population different from the Eastern Shore of Virginia's general population (see Online Appendix B, Table B2). Our sample is older, more male, more self-identified white, more highly educated, and wealthier than the region's general populace (U.S. Census Bureau 2011, 2012). Moreover, our sample had a higher percentage of homeownership than the region's general populace (U.S. Census Bureau 2011). Regarding demographic information not available through the U.S. Census data, 38% of our Northampton respondents and 36% of our Accomack respondents consider themselves natives of the county, and 70% of our Northampton respondents and 52% of our Accomack respondents are bay-side residents.[13] Moreover, across all respondents, the average length of time a respondent has lived on the Eastern Shore is 25 years, and 21% of our respondents stated that there is a 50% or greater chance that their property will be affected by flooding or coastal storm damage in any given year; these percentage values are similar when broken down by county.

We also contacted the planning departments of Northampton and Accomack County for GIS information. GIS analysis allowed us to match each respondent with the parcel density of their home address and the distance of their address from the sea-side coast. Parcel

[10] For Northampton County, we randomly drew 759 addresses (out of 3,922) from the county's voter registration list (the voter registration lists for both counties are generated in August 2013), 151 addresses (out of 448) from a combined membership list of Community Group #1 and Outdoors Group,and 90 addresses (out of 90) from the membership list of Community Group #2. For Accomack County, 700 addresses (out of 13,792) were randomly selected from the county's voter registration list only, 150 addresses (out of 218) were randomly selected from the membership list of Community Group #1, and 150 addresses (out of 186) were randomly selected from the membership list of Outdoors Group. To comply with IRB guidelines to protect respondent's confidentiality, we use generic labels to identify these groups for the purposes of this paper. Community group #2 was not present in Accomack.

[11] Our delivery rate for Community Group #1 and Outdoors Group (combined) was 98 percent for both counties, while the delivery rate to Community Group #2 was 97 percent. For addresses only on the voter registration lists, the delivery rate was 89 percent in Northampton and 87 percent in Accomack.

[12] Our highest useful response rate came from Community Group #1 and Outdoors Group (combined, 60 percent for Northampton, 53 percent for Accomack); this was followed by Community Group #2 (33 percent useful response rate for Northampton) and the voter registration list-only group (26 percent useful response rate for Northampton, 24 percent useful response rate for Accomack).

[13] The distribution between bay-side and sea-side may be due to the larger portion of buildable land on the bay-side compared to the sea-side, along with the historic importance of sheltering from storms on the bay-side.

(a)

Suppose that, according to the best scientific data available, there is expected be an increase in the frequency, intensity, and inland reach of coastal floods over the next 50 years. If this holds true, **9,500 acres** of sea side coastal land in your county would most likely flood and potentially turn into saltmarsh over 50 years. *Suppose* that to manage this flooding, your county will enact a management plan to protect a portion of the county's mainland coast on the sea side.

Suppose your county has proposed two management plans for you to vote on. Please read the information about both plans below and indicate which plan, if either, you would vote to implement if they were the only choices:

	PLAN A	PLAN B	NO ACTION
Total area of coastal land managed to help protect against likely flooding:	6,000 out of 9,500 acres (63% of coastal land expected to be flooded)		No management plan is undertaken. 9,500 acres are expected to flood and will potentially turn into saltmarsh over 50 years. Saltmarsh could provide shoreline protection, wildlife habitat, and/or any of the other benefits listed on page 4 of this survey.
Your county would manage this area of land, along the coastline, by…	…building conventional protection — like seawalls	…building alternative protection — like "living shorelines"	
Managers would choose the locations of coastal land to manage so that the following would most likely not flood after the plan is implemented:	• 3,850 out of 7,000 acres (55%) of ***Forest and Un-Farmed Fields*** • 1,400 out of 1,500 acres (93%) of ***Crop Land and Pasture*** • 750 out of 1,000 acres (75%) of ***Village/Business/Residential***	• 4,000 out of 7,000 acres (57%) of ***Forest and Un-Farmed Fields*** • 1,000 out of 1,500 acres (67%) of ***Crop Land and Pasture*** • 1,000 out of 1,000 acres (100%) of ***Village/Business/Residential***	
Cost to your family, in new taxes, to pay the County's share of the expenses for this plan: **(Your taxes are 100% guaranteed to pay for this plan)**	$75 per year for 5 years ($375 total)	$75 per year for 5 years ($375 total)	
Acc LC V #1 Q #1	☐ I would vote for **Plan A** and pay **$75** in additional taxes per year for five years (**$375 total**).	☐ I would vote for **Plan B** and pay **$75** in additional taxes per year for five years (**$375 total**).	☐ I would **not** vote for **either** Plan A or Plan B and pay **$0** in additional taxes.

(b)

Suppose that, according to the best scientific data available, there is expected be an increase in the frequency, intensity, and inland reach of coastal floods over the next 50 years. If this holds true, **9,500 acres** of sea side coastal land in your county would most likely flood and potentially turn into saltmarsh over 50 years. *Suppose* that to manage this flooding, your county will enact a management plan to protect a portion of the county's mainland coast on the sea side.

Suppose your county has proposed two management plans for you to vote on. Please read the information about both plans below and indicate which plan, if either, you would vote to implement if they were the only choices:

	PLAN A	PLAN B	NO ACTION
Total area of coastal land managed to help protect against likely flooding:	3,000 out of 9,500 acres (32% of coastal land expected to be flooded)		No management plan is undertaken. 9,500 acres are expected to flood and will potentially turn into saltmarsh over 50 years. Saltmarsh could provide shoreline protection, wildlife habitat, and/or any of the other benefits listed on page 4 of this survey.
Your county would manage this area of land, along the coastline, by…	…building conventional protection — like seawalls	…building conventional protection — like seawalls	
Managers would choose the locations of coastal land to manage specifically to…	**…minimize the negative impact on** these environmental benefits: **(1)** Removal of excess nutrients from coastal waters **(2)** Stabilization of sediments that cloud coastal waters **(3)** Saltmarsh buildup to combat coastal flooding	**…minimize the negative impact on** these environmental benefits: **(1)** Removal of excess nutrients from coastal waters **(2)** Undeveloped landscape views for local quality of life **(3)** Maintenance of the historic Eastern Shore culture	
Cost to your family, in new taxes, to pay the County's share of the expenses for this plan: **(Your taxes are 100% guaranteed to pay for this plan)**	$45 per year for 5 years ($225 total)	$45 per year for 5 years ($225 total)	
Acc Eco V #2 Q #5	☐ I would vote for **Plan A** and pay **$45** in additional taxes per year for five years (**$225 total**).	☐ I would vote for **Plan B** and pay **$45** in additional taxes per year for five years (**$225 total**).	☐ I would **not** vote for **either** Plan A or Plan B and pay **$0** in additional taxes.

Fig. 1 Choice questions examples

density is calculated as the kernel density[14] showing how many other properties are in the neighborhood, while the distance to the coast measures the distance from the parcel polygon to the nearest sea-side coast.

To get indicators of the Eastern Shore residents' environmental attitudes, we conducted exploratory factor analysis (Fabrigar et. al. 1999; Basilevsky 2009) for the Likert Scale questions in Survey Section one. The factor analysis retained four factors, and a varimax rotation is performed on these four factors, which gives us the rotated factor pattern and individual factor scores. Based on the rotated factor pattern (see details in Online Appendix C), we interpret the factor score 1, 2, 3, and 4 as measuring a respondent's attitudes favoring a traditional livelihood, maintenance of the local environment, property protection, and economic development, respectively.

After data aggregation and factor analysis, we have thirteen scenario attributes (S_j) for the choice analysis and seventeen individual characteristics (Z_n) for the class membership analysis. The summary statistics for these variables are shown in Table 1.

4 Results

4.1 Baseline Results—The Latent Class Model Estimates

All regressions are conducted on the sample presented in Table 1. We employ the latent class (LC) logit model as our baseline model. We acknowledge that there is no single criterion to choose an optimal class number (segment number), and we use the widely accepted information criteria AIC, BIC, and CAIC (Akaike 1998; Schwarz 1978; Bozdogan 1987) as the measure to decide the preferred class number here (Swait 1994; Boxall and Adamowicz 2002; Burton and Rigby 2009). Starting from models with the full set of parameters (referred to as Full in Table 2) including all the presented variables in Table 1, we calculated information criteria for latent class models with 2, 3, 4, and 5 segments. The statistics of these LC models are shown in Table 2, from which we can see that a model with four segments is preferred according to BIC and CAIC. Also, we list statistics for models that might be employed later in Table 2, which suggest that the 4-segment structure is consistently preferred across highly-restricted LC models and DHLC models.

Since this study plans to estimate probability models with relatively complex structures (i.e., blended hurdle and latent class structure), including all the available variables into the final models would not be wise due to the computational difficulty and it is, therefore, important to decide the parsimonious specification. For the sake of comparison, we consider parsimonious specifications not only for the finalmodels but also for the baseline models. We pick a parsimonious specification for the 4-segment LC model through the following steps and keep using these chosen variables for the DHLC models. First, since some demographics could be highly correlated with the factor scores, excluding those demographics that are insignificant across all membership equations (including Accomack, Years living on the Eastern Shore, Sea-side resident, and Own home) will avoid computational difficulties while losing little in statistical fit. Second, to further revise the variable set

[14] To calculate Kernel density, a smoothly curved surface is fitted over each point. Conceptually, the surface value generated by a point is highest at the location of the point and diminishes with increasing distance from the point. The density at each output cell is calculated by adding all the kernel surface values in the cell. The unit of employed Kernel density is counts per square mile.

Table 1 Summary statistics

Variable name	Description	Mean	Standard deviation
Option attributes	*No. of options = 14,280*		
Cost	Cost of the plan; 0, 15, 30, 45, 60, 75 \$/year	30.00	28.06
Living shoreline (LS)	1 for Alternative coastline; 0, otherwise	.333	.471
Status quo (ASC)	1 for no protection; 0, otherwise	.333	.471
Protected acreage high	1 for a high total acreage; 0, otherwise	.333	.471
Village/Busi/residental	Protected VBR acres; 25–100 for Northampton; 250–1000 for Accomack	116.00	258.12
Cropland and pasture	Protected farm acres; 0–375 for Northampton; 0–1400 for Accomack	152.41	348.28
Habitat and wildlife	1 if ES 1 listed; 0, otherwise	.140	.347
Removal of excess nutrients	1 if ES 2 listed; 0, otherwise	.146	.353
Stabilization of sediments	1 if ES 3 listed; 0, otherwise	.139	.346
Protection against waves and salt spray	1 if ES 4 listed; 0, otherwise	.147	.354
Saltmarsh buildup to combat flooding	1 if ES 5 listed; 0, otherwise	.141	.348
Undeveloped landscape views	1 if ES 6 listed; 0, otherwise	.147	.354
Maintenance of the historic culture	1 if ES 7 listed; 0, otherwise	.140	.347
Individual attributes	*N = 595*		
Female	1 if respondent is female; 0, otherwise	.432	.496
Elder	1 if respondent older than 50; 0, otherwise	.834	.373
Accomack	1 if respondent live in Accomack; 0, otherwise	.508	.500
Years living on the east shore	Years living here; continuous	30.74	22.60
Sea-side resident	1 if live on the sea-side instead of bay-side; 0, otherwise	.608	.489
Own home	1 if respondent owning home; 0, otherwise	.882	.322
High school or less	1 if education lower than college; 0, otherwise	.205	.404
Annual income < 50 k	1 if respondent having income less than 50 k \$/year; 0, otherwise	.245	.431
White	1 if respondent's race is white; 0, otherwise	.787	.410
Environment maintenance score	Factor score 2 from Likert scale questions, related to environment maintenance; continuous	.000	1.00
Property protection score	Factor score 3, related to property or resource protection; continuous	.000	1.00

Table 1 (continued)

Variable name	Description	Mean	Standard deviation
Economic development score	Factor score 4, related to local economy; continuous	.000	1.00
Traditional livelihood score	Factor score 1, related to traditional livelihood; Continuous	.000	1.00
Parcel density	Kernel density of parcel points; continuous	214.45	189.69
Distance to the coast	Nearest distance to the sea-side coast, in hundred meters; Continuous	5.741	3.201
Geographic missing	No geographic attributes available; 0/1	.257	.437

Table 2 Model statistical fit indicators (2–5 segments)[a]

Latent class models	Full	Full	Full	Full	P (D + A + G)	P (D + A)	P (D)
Number of segments	2	3	4	5	4	4	4
LL[b]	−3565.20	−3354.79	−3214.21	−3160.72	−3246.62	−3258.34	−3301.30
K	44	75	106	137	91	82	70
AIC[b]	7218.40	6859.58	6640.43	6595.44	6675.24	6680.68	6742.60
BIC[b]	7411.50	7188.72	7105.62	7196.68	7074.60	7040.55	7049.80
CAIC[b]	7455.50	7263.72	7211.62	7333.68	7165.60	7122.55	7119.80
Latent class models With NP restricted[c]	P (D + A)		P (D + A)		P (D + A)		P (D + A)
Number of segments	2		3		4		5
LL[b]	−3620.339		−3416.95		−3273.99		−3219.61
K	24		47		70		93
AIC[b]	7288.68		6927.90		6687.98		6625.22
BIC[b]	7394.00		7134.16		6995.18		7033.35
CAIC[b]	7418.00		7181.16		7065.18		7126.35
Double hurdle latent class models[d]	P (D + A)		P (D + A)		P (D + A)		P (D + A)
Number of segments	2		3		4		5
LL[b]	–		−3493.35		−3282.56		−3227.57
K	–		46		69		92
AIC[b]	–		7078.70		6703.11		6639.14
BIC[b]	–		7280.57		7005.92		7042.89
CAIC[b]	–		7326.57		7074.92		7134.89

[a]Estimations are based on 4760 choices from 595 (N) survey respondents. Model specification P means parsimonious model, D means including demographics, A means including factor scores indicating environmental attitudes, and G means including geographic variables

[b]LL is the log-likelihood values at convergence. K is the number of parameters. AIC is Akaike information criterion calculated as $2\,K - 2 \times LL$. BIC is Bayesian Information Criteria calculated as $\ln(N) \times K - 2 \times LL$. CAIC is Consistent Akaike Information Criteria calculated as $(\ln(N) + 1) \times K - 2 \times LL$

[c]This panel of restricted latent class models explores the better statistical performance of latent class models by restricting the choice equation non-participation class to only one parameter—status quo alternative specific constant

[d]This panel of double hurdle latent class models with their first hurdles represents the serial non-participants, so their number of segments are calculated as number of latent classes plus one. No 2-segment double hurdle latent class model is estimated, since it only allows one class beyond the hurdle structure (requires no latent class structure)

to be employed in the main analysis, we use information criteria to compare multiple parsimonious 4-class models. These parsimonious 4-class models could include three groups of variables (after the purge in the first step): basic demographics (D),[15] attitudes (A), and

[15] That is, the remaining demographics after purging demographics that are insignificant across all classes.

geographic attributes (G). Table 2 presents the results for three parsimonious specifications for the 4-class model, including a model with all leftover variables (D + A + G), with basic demographics and attitudes (D + A), and with only basic demographics (D). We can see that purging variables with endogeneity (Step one) or major collinearity (Step two) lowers all the information criteria (Table 2, D + A + G vs. Full), and the deletion of geographic variables lowers BIC and CAIC again (Table 2, D + A vs. D + A + G). However, further deletion of factor scores indicating environmental attitudes would cause a major increase in AIC and a minor increase in BIC (Table 2, D vs. D + A). Therefore, the preferred parsimonious specification for the 4-segment class membership equations will include the basic demographics (female, elder, high school or less, annual income less than 50 k, and white) and factor scores indicating environmental attitudes (environment maintenance score, property protection score, economic development score, traditional livelihood score). That is to say, both the 4-segment LC models and the DHLC models in the remainder of this paper employ this parsimonious specification (D + A) unless noted differently.[16]

Table 3 reports the results from the parsimonious LC model with four segments. We can see that the survey respondents can be classified into four divergent classes, with class 4 taken as the reference class. Respondents that are male, self-identified as non-white, with a lower educational attainment level, a lower environmental maintenance score, and a higher traditional livelihood score are more likely to fall in class 1. From the choice equation, we see that class 1 respondents have a quite sizable and significant coefficient on the status quo dummy with only saltmarsh building as a significant attribute of a preferred plan, indicating they are most likely to choose the status quo option. Therefore, we call class 1 **the non-participant group (NP)**. Respondents in class 2 tend to have a lower environment maintenance score and a higher property protection score, as compared to other respondents, and they are more likely to choose options with less cost, higher acreage of protected village/business/residential land, higher acreage of protected farmed land, and ecosystem services related to the environment, while significantly preferring living shoreline to status quo. Thus, we call class 2 **the moderate environmentalist group (ModEnv).** Respondents with a lower environment maintenance score and a higher property protection score are more likely to be in class 3, and we can see that their decisions are mostly based on cost (they have the most sizable and significant cost coefficient and many fewer other attributes being significant, compared to other groups). Therefore, we call class 3 **the economy group (Economy)**. With the class equations of the three classes mentioned above, we can back up the features of respondents in the reference class (class 4), which would be a higher environment maintenance score and a lower property protection score. Respondents in class 4 prefer to choose the status quo, living shoreline, and options with ecosystem services benefiting the environment (e.g., habitat and wildlife for future generations). However, class 4 has a quite small and insignificant cost coefficient, meaning people in class 4 do not appear to make decisions based on cost. Thus, class 4 is called **the pro-nature group (ProNature)**. One thing that should be emphasized is that the pro-nature group's tendency to ignore costs implies that we cannot effectively estimate their

[16] Note that the presented process deciding the final variable set relies on the 4-segment latent class model, but the 4-segment structure is decided with the full set of variables. However, we can show statistical evidence that, with the final parsimonious set, the preferred baseline latent class model is still with four segments (these results are available upon request, and Table 2 also show that, with the final variable set, the 4-segment structure is preferred consistently in highly restricted latent class models and double hurdle models). Moreover, the variable choices only make minor changes to the statistics, comparing with the class structure. That is to say, we generally do not need to compare different specifications across different class structures.

willingness to pay, though this behavior can be explained in different ways. It is likely that the range of proposed costs was low enough to be not critical for these respondents or that these respondents are so strongly in favor of environmental protection that they do not care about the costs, at least in the relevant range used in this survey.

Several additional specification checks are conducted (see details in Online Appendix D for checks concerning county and question set heterogeneities), among which the most important one concerns whether the different expressions for the ecosystem services ("minimize the negative impacts on" in a living shoreline option while "enhance or strengthen" in a seawall option) would make a fundamental difference in the way that participants value each ES. We additionally interact all ESs with the Living Shoreline dummy in a conditional logit model, which is presented in Table D5 of Online Appendix D. We can observe that, in the conditional logit model, most (five out of seven) of the coefficients of interactions are not significant, and the significant ones (ES 6 and ES 7) have mixed directions,[17] suggesting that the respondents do not consistently value ESs more (or less) highly in the living shoreline scenarios. More importantly, when our baseline LC specification includes the interactions between ESs and living shoreline, the model doesn't fit significantly better (LR test p value = 0.5965), and the information criteria increase substantially (BIC = 7258.93, CAIC = 7392.93). Therefore, the effect of different expressions for the ecosystem services can be effectively (in terms of statistical fit) modeled by the living shoreline dummy without interactions, and the main specifications will not include these interactions.

4.2 The Double Hurdle Latent Class Estimates

To formally deal with the serial non-participation issue, we implement the double hurdle latent class logit model proposed above. In accordance with the 4-segment latent class model, we assume that there are three latent classes of participants and one serial non-participation group. Table 4 reports the results from the DHLC model. From the regression results, we can tell that among the four classes in the LC model, **the ModEnv group, the Economy group,** and **the ProNature group** are maintained as participant groups by the double hurdle model, while **the NP group** is separated out as **the serial non-participation group (SNP)**. Though the parameter estimates of the three participant classes are changed to some extent from Table 3, the general pattern of their features and their preferences toward coastal plans remain the same. We find that the SNP is identified somewhat differently compared with the NP group in the LC model, but these differences might be led by different model structures (multinomial logit versus hurdle) and cannot be compared directly. Moreover, we do find the estimated share of SNP (0.226) is lower than the share of NP (0.282) under the LC model.

We argue that the DHLC model fits the data generation process better since the serial non-participants do not fit in the compensatory utility framework (where the respondents evaluate trade-offs between choice attributes) assigned by the baseline unrestricted LC model, and we list the statistical evidence in Table 5. Table 5 shows the information criteria for both models and the Vuong non-nested test results. Though the AIC value suggests that the baseline LC model is marginally better, the BIC and CAIC values suggest that the DHLC model is the better choice in terms of reducing information loss. To test whether the DHLC model has a significantly higher statistical fit than the baseline LC model, we

[17] Also, a joint likelihood ratio test of the seven interactions return a p-value of 0.0931, suggesting they are not significantly jointly different from zero at the 5-percent significance level.

Table 3 Four-segment latent class logit model[a]

Variable (choice eq.)	Class 1 (NP)	Class 2 (ModEnv)	Class 3 (Economy)	Class 4 (ProNature)
Cost ($-\beta_{ky}$)	−0.0254	−0.00569**	−0.0311***	−0.000905
	(0.0238)	(0.00176)	(0.00483)	(0.00358)
Living shoreline (LS)	0.986	0.683***	0.489**	3.974***
	(0.636)	(0.0868)	(0.184)	(0.328)
Status quo (ASC)	5.019***	−2.722***	−0.273	2.315***
	(0.777)	(0.499)	(0.338)	(0.364)
Protected acreage high	0.571	−0.477	0.168	−0.0380
	(0.479)	(0.410)	(0.203)	(0.231)
Village/business/residential	−0.0000828	0.00177***	0.000450	0.000873*
	(0.00182)	(0.000309)	(0.000407)	(0.000433)
Cropland and pasture	0.00133	0.000210	−0.000149	−0.000146
	(0.00161)	(0.000123)	(0.000264)	(0.000209)
Habitat and wildlife (ES 1)	−0.687	0.382*	0.0425	0.817***
	(1.322)	(0.164)	(0.216)	(0.200)
Removal of excess nutrients (ES 2)	−0.719	0.201	−0.243	0.548*
	(0.921)	(0.177)	(0.244)	(0.221)
Stabilization of sediments (ES 3)	0.242	0.0213	0.0937	0.290
	(0.756)	(0.176)	(0.220)	(0.245)
Protection against salt spray (ES 4)	−0.634	0.264	0.127	0.456
	(1.060)	(0.171)	(0.212)	(0.237)
Saltmarsh buildup to combat coastal flooding (ES 5)	1.455*	0.561***	0.295	0.677***
	(0.680)	(0.169)	(0.207)	(0.203)
Undeveloped landscape views (ES 6)	−0.395	−0.339*	−0.655**	−0.499*
	(0.876)	(0.171)	(0.237)	(0.231)
Maintenance of the historic culture (ES 7)	1.190	−0.444*	−0.229	−0.623**
	(1.173)	(0.173)	(0.227)	(0.222)
Class share[b]	0.282	0.372	0.132	0.214
Membership eq	**Class 1**	**Class 2**	**Class 3**	**Reference**
Female	−0.595*	−0.436	−0.436	–
	(0.290)	(0.267)	(0.382)	
Elder	−0.414	−0.122	0.712	–
	(0.357)	(0.336)	(0.639)	
High school or less	1.342**	0.512	0.759	–
	(0.475)	(0.482)	(0.565)	
Annual income < 50 k	0.124	−0.0836	0.224	–
	(0.345)	(0.332)	(0.430)	
White	−0.984**	−0.169	−0.658	–
	(0.369)	(0.356)	(0.513)	
Environment maintenance score	−1.056***	−0.752***	−1.157***	–
	(0.170)	(0.165)	(0.240)	
Property protection score	−0.0482	0.322*	0.550*	–
	(0.149)	(0.144)	(0.231)	

Table 3 (continued)

Membership eq	Class 1	Class 2	Class 3	Reference
Economic development score	−0.256	−0.0867	−0.358	–
	(0.148)	(0.142)	(0.203)	
Traditional livelihood score	0.332*	0.0271	0.294	–
	(0.151)	(0.137)	(0.199)	
LL = −3258.342, AIC = 6680.684, BIC = 7040.546, CAIC = 7122.546				

[a]Estimation is based on 4760 choices from 595 survey respondents. Standard errors are in parentheses. *, **, *** indicate $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively. Constant is added to each membership equation, but not displayed

[b]The class shares are mean predicted class membership probabilities based on the membership equations

employ a Vuong nonnested hypothesis test (Vuong 1989; von Haefen et al. 2005; Burton and Rigby 2009), since the two models cannot be transformed into each other by simply adding variables or imposing constraints on the parameters (hence LR tests for nested models are inappropriate). Based on the Vuong test of the null hypothesis that the DHLC is statistically equivalent to the 4-segment unrestricted LC model, we are able to reject that null hypothesis at a significance level of 0.1. However, we note that we have argued that DHLC would fit the data generating process better than the unrestricted LC model, so that the Vuong test could be evaluated as a one-tailed test rejecting the null hypothesis at $p < 0.05$, which allows us to conclude that the DHLC model is preferred to the baseline unrestricted LC model with a significance level of 0.05.

To further investigate the performance regarding statistical fit associated with the double hurdle structure, we consider how similarly a latent class model without hurdle structure can perform to a double hurdle model. Burton and Rigby (2009) suggested that an LC model with the membership equation of the non-participation group restricted to only several (three in their case) would-be significant parameters (i.e., significant in the baseline unrestricted LC model) performs strictly better in terms of statistical fit than a double hurdle random coefficient model. We restrict the baseline LC model so that the NP group only includes status quo ASC in its choice equation (detailed estimates are shown in Table 6), and compare it with the DHLC model. The Vuong test fails to reject the null hypothesis of equivalence at any conventional significance level (Vuong statistic: 0.7887), whether we apply either a one-tailed or two-tailed criteria, which suggest that the DHLC model performs statistically the same as the restricted LC model in terms of fitting the data generation process. This relatively highly-restricted LC model requires a prior definition of non-participation, and, even though, the LC model does not show significant statistical dominance over the hurdle structured LC model.

As a conclusion, our regression results suggest that the double hurdle latent class model is preferred to an unrestricted latent class model when a substantial proportion of the respondents act as non-participants, but a latent class structure may have similar performance regarding statistical fit if it is restricted with a prior definition of non-participation. Moreover, two major differences in parameter estimates between the DHLC and LC model should be highlighted: the membership equations for the non-participation group are estimated somewhat differently in these two models, and the parameter estimates in choice equations are also slightly different across all classes.

Table 4 Double hurdle latent class model-unrestricted[a]

Variable (choice eq.)	ModEnv	Economy	ProNature
Cost ($-\beta_{ky}$)	−0.00627***	−0.0315***	−0.00105
	(0.00172)	(0.00448)	(0.00350)
Living shoreline (LS)	0.662***	0.573***	3.837***
	(0.0873)	(0.170)	(0.302)
Status quo (ASC)	−2.470***	0.522	2.172***
	(0.388)	(0.287)	(0.376)
Protected acreage high	−0.418	0.297	−0.0159
	(0.338)	(0.177)	(0.216)
Village/business/residential	0.00177***	0.000204	0.000832*
	(0.000309)	(0.000385)	(0.000422)
Cropland and pasture	0.000207	0.0000887	−0.000152
	(0.000121)	(0.000265)	(0.000208)
Habitat and wildlife (ES 1)	0.371**	0.0481	0.809***
	(0.136)	(0.202)	(0.197)
Removal of excess nutrients (ES 2)	0.204	−0.341	0.560**
	(0.152)	(0.236)	(0.216)
Stabilization of sediments (ES 3)	0.0282	−0.0326	0.239
	(0.152)	(0.213)	(0.234)
Protection against salt spray (ES 4)	0.272	0.0857	0.397
	(0.142)	(0.205)	(0.231)
Saltmarsh buildup to combat coastal flooding (ES 5)	0.562***	0.537**	0.618**
	(0.143)	(0.196)	(0.200)
Undeveloped landscape (ES 6)	−0.334*	−0.681**	−0.483*
	(0.146)	(0.231)	(0.223)
Maintenance of the historic culture (ES 7)	−0.448**	0.0808	−0.648**
	(0.146)	(0.215)	(0.218)
Class share[b]	0.383	0.171	0.220
Membership(hurdle) eq	**ModEnv**	**Economy**	**Hurdle (SNP)**
Female	−0.470	−0.636	−0.104
	(0.287)	(0.366)	(0.127)
Elder	−0.0871	0.767	−0.367*
	(0.456)	(0.685)	(0.158)
High school or less	0.430	0.742	0.506***
	(0.476)	(0.528)	(0.147)
Annual income < 50 k	−0.136	0.270	−0.0169
	(0.341)	(0.407)	(0.144)
White	−0.286	−0.748	−0.455**
	(0.569)	(0.604)	(0.146)
Environment maintenance score	−0.781***	−1.108***	−0.221***
	(0.166)	(0.205)	(0.0620)
Property protection score	0.326*	0.232	−0.138*
	(0.144)	(0.184)	(0.0615)
Economic development score	−0.0417	−0.285	−0.108
	(0.150)	(0.187)	(0.0592)

Table 4 (continued)

Membership(hurdle) eq	ModEnv	Economy	Hurdle (SNP)
Traditional livelihood score	0.0470	0.452*	0.108
	(0.141)	(0.187)	(0.0617)
LL = −3282.556; AIC = 6703.112, BIC = 7005.923, CAIC = 7074.923			

[a]Estimation is based on 4760 choices from 595 survey respondents. Standard errors are in parentheses. *, **, *** indicate $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively. Constant is added to the membership equations, but not displayed

[b]The class shares are mean predicted class membership probabilities. Class share of SNP (hurdle) = 0.227

Table 5 Statistical comparison of the latent class models and double hurdle latent class models[a]

Model	4-segment LC	DHLC	4-segment LC Restricted
LL[b]	−3258.34	−3282.56	−3273.99
K[b]	82	69	70
AIC[b]	6680.68	6703.11	6687.98
BIC[b]	7040.55	7005.92	6995.18
CAIC[b]	7122.55	7074.92	7065.18
Vuong tests[c] (LC, DHLC)	Vuong test statistic = −1.6497 p value (H_0: Vuong $\geq$ 0) = 0.0495 p value (H_0: Vuong = 0) = 0.0990		Vuong test statistic = 0.7887 p value (H_0: Vuong $\geq$ 0) = 0.7849 p value (H_0: Vuong = 0) = 0.4302

[a]Estimations are based on 4760 choices from 595 (N) survey respondents, and all models have the same set of covariates unless denoted

[b]LL is the log-likelihood values at convergence. K is the number of parameters. AIC is Akaike information criterion calculated as 2 K − 2 × LL. BIC is Bayesian Information Criteria calculated as ln(N) × K − 2 × LL. CAIC is Consistent Akaike Information Criteria calculated as (ln(N) + 1) × K − 2 × LL

[c]Vuong test statistic is constructed as LR/($\omega_N \sqrt{N}$), where LR equals to $LL_{LC} - LL_{DHLC} - \ln(\mathrm{N})\left(K_{LC} - K_{DHLC}\right)/2$, and ω_N^2 is the sample variance of the pointwise log-likelihood ratio. The test result of null hypothesis Vuong > = 0 (H_a: Vuong < 0) suggests the LC model is the same as or preferred to DHLC if not rejected, while the left-hand test rejects the null hypothesis with a significance level of .05. The test result of null hypothesis Vuong = 0 (H_a: Vuong ≠ 0) suggests the LC model performs statistically the same as the DHLC model if not rejected, while the left-hand test rejects with a significance level of .1

4.3 Willingness to Pay Measures

To further learn the welfare implications of the segmentation structure and statistical improvement presented above, we move on to welfare analysis based on the DHLC model

Table 6 Four-segment latent class logit model-restricted[a]

Variable (choice eq.)	Class 1 (NP)	Class 2 (ModEnv)	Class 3 (Economy)	Class 4 (ProNature)
Cost ($-\beta_{ky}$)	–	−0.00596***	−0.0324***	−0.000642
		(0.00178)	(0.00526)	(0.00355)
Living shoreline (LS)	–	0.674***	0.570**	3.936***
		(0.0902)	(0.181)	(0.428)
Status quo (ASC)	4.733***	−2.632***	−0.0409	2.289***
	(0.284)	(0.525)	(0.341)	(0.479)
Protected acreage high	–	−0.463	0.234	−0.0289
		(0.371)	(0.200)	(0.236)
Village/business/residential	–	0.00177***	0.000308	0.000874
		(0.000308)	(0.000409)	(0.000470)
Cropland and pasture	–	0.000209	−0.0000931	−0.000139
		(0.000123)	(0.000265)	(0.000218)
Habitat and wildlife (ES 1)	–	0.375*	0.0483	0.826***
		(0.170)	(0.214)	(0.209)
Removal of excess nutrients (ES 2)	–	0.205	−0.323	0.567*
		(0.180)	(0.244)	(0.228)
Stabilization of sediments (ES 3)	–	0.0231	0.0505	0.273
		(0.182)	(0.217)	(0.270)
Protection against salt spray (ES 4)	–	0.268	0.0914	0.442
		(0.174)	(0.204)	(0.270)
Saltmarsh buildup to combat coastal flooding (ES 5)	–	0.557**	0.420*	0.659**
		(0.170)	(0.206)	(0.219)
Undeveloped landscape views (ES 6)	–	−0.339	−0.689**	−0.495*
		(0.180)	(0.238)	(0.229)
Maintenance of the historic culture (ES 7)	–	−0.447*	−0.0939	−0.636**
		(0.180)	(0.227)	(0.222)
Class share[b]	0.267	0.376	0.142	0.215
Membership eq	**Class 1**	**Class 2**	**Class 3**	**Reference**
Female	−0.574	−0.446	−0.508	–
	(0.294)	(0.277)	(0.365)	
Elder	−0.455	−0.133	0.721	–
	(0.363)	(0.341)	(0.506)	
High school or less	1.382**	0.538	0.777	–
	(0.467)	(0.470)	(0.533)	
Annual income < 50 k	0.0725	−0.0957	0.241	–
	(0.350)	(0.333)	(0.419)	
White	−1.039**	−0.213	−0.739	–
	(0.395)	(0.359)	(0.454)	
Environment maintenance score	−1.066***	−0.757***	−1.113***	–
	(0.170)	(0.164)	(0.243)	
Property protection score	−0.0455	0.308*	0.381	–
	(0.157)	(0.149)	(0.216)	

Table 6 (continued)

Membership eq	Class 1	Class 2	Class 3	Reference
Economic development score	−0.254	−0.0757	−0.331	–
	(0.164)	(0.155)	(0.222)	
Traditional livelihood score	0.315*	0.0265	0.356	–
	(0.151)	(0.138)	(0.193)	
LL = −3273.992, AIC = 6687.984, BIC = 6995.184, CAIC = 7065.184				

[a]Estimation is based on 4760 choices from 595 survey respondents. Standard errors are in parentheses. *, **, *** indicate $p<0.1$, $p<0.05$, $p<0.01$, respectively. Constant is added to each membership equation, but not displayed

[b]The class shares are mean predicted class membership probabilities based on the membership equations

Table 7 Marginal willingness to pay from the latent class and double hurdle latent class model[a]

Marginal WTP	4-segment LC		DHLC	
Variable	Economy	ModEnv	Economy	ModEnv
Living shoreline (LS)	15.74***	120.07***	18.20***	105.56***
	(6.54)	(42.15)	(5.71)	(33.56)
Protected acreage high	5.39	−83.77	9.42	−66.68
	(6.69)	(76.00)	(5.77)	(56.81)
Village/busi/residental	.0145	.311***	.0065	.282***
	(.0133)	(.111)	(.0122)	(.0909)
Cropland and pasture	–.0048	.0370	.0028	.0330
	(.0085)	(.0260)	(.0084)	(.0224)
Habitat and wildlife (ES 1)	1.368	67.15*	1.528	59.07**
	(6.986)	(37.42)	(6.416)	(27.29)
Removal of excess nutrients (ES 2)	−7.820	35.34	−10.83	32.53
	(7.829)	(33.00)	(7.52)	(25.15)
Stabilization of sediments (ES 3)	3.015	3.739	−1.036	4.487
	(7.022)	(30.939)	(6.771)	(24.22)
Protection against salt spray (ES 4)	4.075	46.37	2.720	43.38
	(6.852)	(34.92)	(6.532)	(26.20)
Saltmarsh buildup to combat coastal flooding (ES 5)	9.496	98.61**	17.05**	89.58***
	(6.919)	(43.68)	(6.70)	(32.67)
Undeveloped landscape views (ES 6)	−21.07***	−59.62*	−21.61***	−53.23*
	(7.83)	(33.66)	(7.57)	(27.14)
Maintenance of the historic culture (ES 7)	−7.360	−78.04**	2.565	−71.46**
	(7.476)	(37.37)	(6.798)	(30.57)
Status quo (ASC)	−8.79	−478.37***	16.57	−393.70***
	(10.25)	(154.47)	(10.39)	(112.65)

[a]Estimations are based on 4760 choices from 595 (N) survey respondents N = 595. Standard errors are in parentheses. *, **, *** indicate $p<0.1$, $p<0.05$, $p<0.01$, respectively

with three latent classes (Table 4). The marginal willingness to pay (MWTP) measures for each attribute are given in Table 7, where the results of the LC model with four segments (Table 3) are also presented for comparison. Although the corresponding results for the status quo may not be interpreted as MWTPs, we include them in Table 7 since they indicate the initial valuation of the status quo and will be used in the total WTP estimation below, as suggested by Eq. (16). We can see that the MWTP measures from the DHLC model and the LC model are qualitatively similar, which again suggests the latent segmentation among participants is robust to model specification (i.e., LC or DHLC). Since the cost coefficients of **the ProNature group** are not significant at all in both models (Table 3 and 4), and the MWTP estimates based on them are also insignificant and unreliable, Table 7 omits results from **the ProNature group**. **The Economy group** shows significantly positive MWTP for living shoreline and significantly negative MWTP for undeveloped landscape (ES 6). The MWTPs of **the Economy group** are quite close to zero, compared to the MWTPs of **the ModEnv group**. **The ModEnv group** not only shows much higher MWTPs on the attributes valued by the Economy group but also shows significantly positive MWTPs on the following attributes: acreage of protected Village/Business/Residential land, habitat and wildlife (ES 1), saltmarsh buildup to combat coastal flooding (ES 5), and significantly negative MWTPs on SQ and maintenance of historic Eastern Shore culture (ES 7).

Though the MWTPs from the LC and DHLC models are mostly similar, these two models do have different implications regarding the estimation of total WTPs. The class-specific total WTP for both the LC model and the DHLC model can be calculated based on Eq. (16), and the total WTP measure can be computed as a weighted (by segment membership) average of class-specific WTPs (Boxall and Adamowicz 2002). We set up eight scenarios as described in Online Appendix E to show how to calculate these WTP measures. We calculate the welfare measures, including both the class-specific WTP (Table 8, more results are discussed in Online Appendix E) and total WTP, for the changes from the status quo to these given scenarios.

To recover the sample WTP, we need to infer the willingness to pay measures of those groups who do not explicitly conduct trade-offs between cost and other attributes and hence do not show their compensatory values. This inference concerns two groups of respondents: the serial non-participants and the pro-nature group (for whom we have an insignificant, positive, and close-to-zero cost coefficient). For this analysis, we assume that the pro-nature group's value can be reasonably well approximated by the average of the WTP estimates for the other participating groups[18] since they seem to be willing to accept alternative plans and pay for them. However, the reasonable welfare imputation for a serial non-participant is hard: as suggested by von Haefen et al. (2005), it depends on the individuals' reason for not participating. If we assume that all serial non-participants are driven by the reluctance to accept climate change science or related government intervention (Shapiro 2016), it may be appropriate to assign zero[19] to the welfare measure of the serial non-participation group. Alternatively, if non-participation behavior is motivated by cognitive limitations (because of the complexity of the choice questions), or time limitations that keep individuals from evaluating the choices fully, it may be appropriate to assume that the non-participants would have the same average value as the participants

[18] We acknowledge that this assumption might be conservative, since WTP of the pro-nature group might be higher than the other participating groups. Nonetheless, we cannot infer their maximum values from this study.

[19] Arguably, their WTP for a change that is against their will could be negative. But since we cannot infer their exact WTP from our survey study, we follow the literature to use zero to represent their WTP.

have. It may be reasonable[20] to assume the serial non-participation group is a result of a mixture of these factors, and hence imputing an average value and imputing a zero value would serve, respectively, as an estimate of the upper and lower bound of the true sample total WTP. In any event, it is not our intent to claim estimates based on these assumptions would be definitive; rather, these extremes provide some foundation to assess the sensitivity of total WTP to the treatment of non-participants.

Based on the conditional probability framework built for our DHLC model, we can predict the expected sample WTPs from the parameter estimates, which are displayed in Table 9. Column 1 reports the expected WTP measure from the novel DHLC model when the analysis ignores the hurdle, meaning assigning average values to the serial non-participants; while column 2 reports the results when the analysis scales the estimates for participants by the participant probability ($1 - \Pr\{SNP\}$) in Eq. (11), thereby imputing zero values to the serial non-participants. Allowing the same assumptions for the latent classes in the LC model in Table 9, Column 3 reports the welfare estimates from the LC model when ignoring the hurdle, and Column 4 reports the results from the LC model when imputing zero values to the non-participants. Moreover, to compare with the widely used random parameter model without hurdle, we add column 5 in Table 9, reporting the corresponding results from a random coefficient logit model (as shown in Online Appendix F, it treats all coefficients except cost as random coefficients). Finally, based on the statistics from the 2010 Census data (U.S. Census Bureau 2011), we build simulated samples (from 5000 repetitions) representing the mean population demographics and calculate the expected total WTPs using the parameter estimates from the DHLC model. These calculations provide insight into the mean WTP estimated for the population of the Eastern Shore.

The differences in estimated total WTPs across models are clear in Table 9. The estimated WTPs from the DHLC model are substantially and consistently lower than those from the LC model under alternative assumptions, while consistently larger than those from the random coefficient model. We first consider the differences between the results from the widely employed random coefficient model and the DHLC model. The estimated average WTPs from the random coefficient model are much lower[21] than the estimates from the LC or DHLC models, which is a result of including serial non-participants whose WTPs would tend to be negative if estimated in a compensatory utility framework using random coefficients. Moreover, the standard deviations from the random coefficient model are substantially higher than that estimated from the LC or DHLC models, which is likely led by the inclusion of the pro-nature group whose WTP measures are quite insignificant.

On the other hand, though the LC model and DHLC model treat the pro-nature group and non-participation group similarly, the LC model gives consistently higher total WTP than the DHLC model does (Table 9). We believe that by modeling serial non-participants within the compensatory utility framework, the LC models could include biases in the choice equations compared with that estimated under the DHLC model, as discussed further in the following section.

After the adjustment based on the population demographics, we observe that the estimated population WTPs are lower than the sampleWTPs from the same DHLC model. As mentioned above, the Eastern Shore's population is younger, less educated, and less wealthy than our respondents. Checking these demographic variables in the hurdle equation

[20] Although the underlying story here is that the serial non-participation is mostly caused by the opposition to climate science or government action instead of pure cognitive difficulties, we cannot exclude the later factor empirically.

[21] This result is consistent with the results presented in von Haefen, et. al. (2005) (when SQ is included).

in Table 4, we can conclude that an average Eastern Shore resident is more likely to be a serial non-participant than an average respondent, and this results in lower WTP estimates for the population. The DHLC approach allows one to conduct the welfare analysis with adjustments for the pro-nature group and the non-participants, and to project the population values through estimated demographic parameters, but these WTP estimates are still based on restrictive assumptions.[22] This fact reinforces the importance of additional research to improve the understanding of how to evaluate the welfare values of serial non-participants.

From the DHLC model and the welfare analysis for the population, we can see that, on average, the Eastern Shore residents' WTP for different coastal climate adaptation plans ranges from about 50 dollars to about 170 dollars per year for five years. They have lower expected WTPs for seawalls (Scenario 1, 3, 5, 7, see Online Appendix E for details) than they do for living shorelines (Scenario 2, 4, 6, 8), given all the other attributes. Focus groups led us to identify the list of ecosystem services. But, consistent with the framework of Johnston and Russell (2011), it appears that not all of these services affected the well-being of all respondents. Statistically significant and positive MWTPs present in ES 1 (habitat and wildlife) and ES 5 (saltmarsh buildup) for the ModEnv group, while these services show no significant MWTPs for the Economy group. In terms of total welfare improvement, certain ecosystem services are important for the presented coastal plans. For instance, when the implementation of a coastal plan considers removal of excess nutrients, stabilization of sediments, and saltmarsh buildup to combat coastal flooding, we estimate a roughly 40% increase in the Eastern Shore residents' WTP.

5 Discussion

The proposed DHLC model provides an answer to the criticism (Burton and Rigby 2009) towards the prior definition of SNP in double hurdle models, since the prior definition doesn't limit the understanding and interpretation of apparent non-participants in DHLC models. Based on our experience with focus groups, respondents who always choose SQ may have one of two different motivations: presenting resistance to government plans (or climate change science) or refusing any coastal plans because of the belief that nature should take its own course (see Yue 2017, p. 54). One may notice that the pro-nature group has a sizable, positive, and statistically significant coefficient on SQ (Table 4), meaning that the respondents in the pro-nature group have a considerable likelihood of choosing SQ. This situation can be linked to a large body of literature showing that respondents may have different motives to disproportionately choose SQ (e.g., Kahneman et al. 1991; Samuelson and Zeckhauser 1988; Meyerhoff and Liebe 2009). We believe that the pro-nature class captures some of the all-status-quo respondents, which hints at the fact that, by modeling with the DHLC approach, we address different drivers of the behavior of individuals choosing all-status-quo responses, permitting flexibility structurally (i.e., allowing an all-status-quo respondent to have the possibility of being addressed by the first hurdle as well as being in one latent class of participants). Also, test results show that the DHLC matches the data generation process well enough to significantly improve the goodness of fit from the baseline unrestricted LC model. Therefore, we believe that the prior definition of SNP is not a disadvantage

[22] One widely perceived concern is that welfare measures from stated preference studies might be subject to hypothetical bias. Though some efforts have been made to reduce hypothetical bias in this study, we cannot claim that the hypothetical bias is totally eliminated.

Table 8 Class-specific willingness to pay measures for scenario 1 and 2[a]

Model	WTP scenarios	ModEnv	NP/SNP (Hurdle)	ProNature	Economy
Latent class model	Scenario#1: Seawalls with a high level of acreage protected, 75 VBR[b], 425 CLP[b], ES[b] 2, 3, and 5				
	Mean	572. 39 \$/year**	−114.69 \$/year	−923.31 \$/year	17.92 \$/year
	Standard Error	174.18	160.77	3828.18	11.88
	95% confidence interval	[229.91, 912.67]	[−429.8, 200.41]	[−8426.4, 6579.8]	[−5.36, 41.21]
	Scenario#2: Living shoreline with a high level of acreage protected, 100 VBR[b], 375 CLP[b], ES[b] 1, 2, and 5				
	Mean	760.68 \$/year**	−115.14 \$/year	4085.93 \$/year	32.62 \$/year**
	Standard Error	234.58	114.99	16,031.22	13.43
	95% confidence interval	[300.92, 1220.45]	[−340.52, 110.25]	[−27,335, 35507]	[6.31, 58.94]
Double hurdle latent class model	Scenario#1: Seawalls with a high level of acreage protected, 75 VBR[b], 425 CLP[b], ES[b] 2, 3, and 5				
	Mean	488. 80 \$/year***	–	−735.87 \$/year	.273 \$/year
	Standard error	127.24	–	2602.14	11.656
	95% confidence interval	[239.40, 738.19]	–	[−5836.0, 4364.2]	[−23.12, 22.57]
	Scenario#2: Living shoreline with a high level of acreage protected, 100 VBR[b], 375 CLP[b], ES[b] 1, 2, and 5				
	Mean	654.33 \$/year***	–	3480.80 \$/year	20.51 \$/year*
	Standard error	173.52	–	11,485.7	11.58
	95% confidence interval	[314.25, 994.42]	–	[−19,031, 25992]	[−2.19, 43.20]

[a]Estimations are based on 4760 choices from 595 (N) survey respondents N = 595. 95% confidence intervals are in parentheses. *, **, *** indicate $p < 0.1$, $p < 0.05$, $p < 0.01$, respectively

[b]VBR means the protected acreage of the village, business, and residential land. CLP represents the protected acreage of cropland and pasture. ES denotes the ecosystem services that are considered in the scenario: ES 1 represents habitat and wildlife for future generations, ES 2 represents removal of excess nutrients from coastal waters, ES 3 represents stabilization of sediments that cloud coastal waters, ES 5 represents saltmarsh buildup to combat coastal flooding (i.e., saltmarsh accretion)

Table 9 Expected willingness to pay

WTP[a] $/year	DHLC[b]		4-segment LC[b]		Random coefficient[b]	DHLC (Population)[c]	
Scenario	Ignoring SNP[d]	Imputing zeros to SNP[d]	Ignoring NP[d]	Imputing zeros to NP[d]		Ignoring SNP	Imputing zeros to SNP
#1 Seawalls, high level of acreage protected, 75 VBR, 425 CLP, ES2, 3, and 5							
	242.47 (59.91)	187.37 (56.40)	430.61 (75.25)	287.96 (94.10)	69.14 (405.08)	111.07 (43.68)	63.62 (30.77)
#2 Living shoreline, high level of acreage protected, 100 VBR, 375 CLP, ES 1, 2, and 5							
	329.62 (79.81)	254.38 (75.11)	575.59 (99.00)	384.82 (125.03)	254.55 (443.60)	157.42 (57.84)	89.78 (41.21)
#3 Seawalls, high level of acreage protected, 50 VBR, 300 CLP, ES 1, 2, and 5							
	264.51 (65.19)	204.36 (61.37)	468.30 (82.38)	313.20 (102.59)	96.18 (405.21)	121.81 (47.48)	69.73 (33.50)
#4 Living shoreline, high level of acreage protected, 50 VBR, 300 CLP, ES 1, 2, and 5							
	321.27 (77.79)	247.94 (73.21)	561.85 (96.56)	375.63 (122.01)	248.38 (442.96)	153.43 (56.37)	87.51 (40.17)
#5 Seawalls, high level of acreage protected, 75 VBR, 425 CLP							
	178.40 (44.52)	137.94 (41.90)	326.73 (57.16)	218.50 (71.43)	−11.98 (399.94)	80.10 (32.59)	45.98 (22.82)
#6 Living shoreline, high level of acreage protected, 100 VBR, 375 CLP							
	237.85 (57.75)	183.59 (54.35)	424.84 (72.07)	283.97 (91.82)	142.64 (438.32)	112.96 (41.87)	64.46 (29.79)
#7 Seawalls, low level of acreage protected, 75 VBR, 425 CLP, ES2, 3, and 5							
	273.29 (68.31)	211.33 (64.28)	491.71 (87.37)	328.91 (108.13)	68.65 (405.00)	122.30 (50.04)	70.22 (35.01)
#8 Living shoreline, low level of acreage protected, 100 VBR, 375 CLP, ES 1, 2, and 5							
	360.44 (88.15)	278.34 (82.97)	636.69 (111.13)	425.77 (139.07)	254.06 (443.46)	168.65 (64.03)	96.39 (45.38)

[a]The total WTP is measured as a payment per year for five years. Standard deviations are in parentheses. The WTPs can be predicted for Accomack and Northampton separately, and these results are available upon request

[b]For the DHLC and LC model, estimates for the realized sample (595 respondents) are averages of individual expected WTPs. The expected WTPs are expectations of class-specific WTPs weighted by each individual's class probabilities. For the random coefficient logit model, 5000 simulations are used to construct the point estimates

[c]Estimates for the population are adjustments of the DHLC results for the respondents, based on the population demographics from the Census data (Table B2) and 5000 simulations

[d]The WTPs imputing zeros to non-participants (SNP or NP) are scaled with individual probabilities of participation. The expected WTPs ignoring non-participants are not scaled, so that the non-participants are imputed with the average expected WTP of the participants. The results ignoring non-participants are interpreted as upper bound estimates of the average WTP, while the results imputing zeros are interpreted as lower bound estimates. Pro-nature groups are not included in the calculation for both the LC and DHLC model (we assume that they can accommodate the averages of the other participating groups)

of the DHLC model. More importantly, the prior definition of SNP employed in this paper is not necessarily the best one (in terms of fitting the data generation process). One can vary the prior definition (e.g., from all-status-quo respondents to six-out-of-eight-status-quo ones) to search for a statistically better performing DHLC model.

Test results also show that, with a prior definition of non-participation, a highly-restricted LC model has a similar performance as the DHLC model in terms of statistical fit. However, one may notice that the parameters in the non-participation choice equations in the LC models are difficult to interpret since these parameters are specified to indicate the status quo level of utility or valuation of various option attributes while the non-participants are not actually providing choices that can support estimation of values. More importantly, incorporating economically meaningless parameters is not harmless to the estimation of the parameters in other equations (i.e., membership equations) or other classes. First, the non-participation group in the restricted or unrestricted LC models captures mostly-status-quo respondents, including those participating ones who actually make trade-offs, nonetheless decide to choose SQ, and end up choosing SQ for most or all questions. Evidence includes that the predicted NP shares in LC models are always larger than the SNP share in the DHLC model, and that some NP choice equations involve significant coefficients other than SQ (e.g., Online Appendix Table D3). The characteristics of these participating mostly-status-quo respondents are captured in the non-participation membership equations of LC models, and thus using these equations to characterize non-participants can yield biased judgments. Second, since the choice equations are not estimated independently, the inclusion of parameters in the non-participation choice equation can bias the estimates of choice equations for other classes. The differences in parameter estimates might seem to be trivial (actually the differences in SQ ASC are not trivial), but they are likely to yield considerable differences in welfare measures. One can tell this from the fact (in Table 9) that the LC model gives consistently and considerably higher total WTP than the DHLC model does.

Despite the aforementioned disadvantages, the LC models are by no means useless in addressing problems from non-participation. The computational difficulty and programming complexity in estimating DHLC models make it time-consuming to vary specifications and detect non-participation patterns with DHLC models, while easily accessible latent class packages using expectation–maximization algorithms make LC models good tools to detect seemingly non-participation patterns in many DCE datasets. Also, in a context where participants are not likely to display mostly-status-quo patterns, the membership segmentation from the LC models could be quite close to that from the DHLC models. These considerations suggest that DHLC models can be generally treated as a revised version of LC models, wherein revisions are designed to address the implications of non-participation behavior.

Another important message from this study is implied in the existence of the pro-nature group: how to define non-participants in a stated preference study. Certainly, we observe different choice patterns for different groups of respondents, including considerable differences in the size and significance of the cost coefficient. Even though the assigned cost range was designed and revised after several rounds of focus groups, the assigned cost can still not be particularly salient for a subgroup of the sample (e.g., the pro-nature group). This observation is analogous to the attribute non-attendance phenomenon in the DCE literature (Scarpa et al. 2012; Glenk et al. 2015), where each participant may focus only on a subset of attributes while making choices. To interpret our results in a manner that might parallel results from an attribute non-attendance model (which we leave outside the scope of this paper), we would say that the economy group may just focus on cost when making their decisions, while the pro-nature group may focus on the attributes closely related to the environment. We believe that a formal definition of non-participants relies on the incentives- or the individual's personal objectives—behind their survey response behavior (Carson and Groves 2007). If the incentives for a specific survey behavior would also drive the same kind of behavior in decision-making external to the survey, then it may not be necessary to claim respondents with such behavior are non-participants. For example, assuming the enthusiasm for environmental protection drives the pro-nature group into making choices without consideration of cost (over the range of cost presented in our DCE), it also is likely to make them willing to pay for the environmental projects at any cost within a reasonable range, and hence we do not define the pro-nature group as non-participants. In contrast, when actually facing sea-level rise, many of the serial non-participants driven by mistrust of government or protest attitudes (Jorgensen et al 1999; Meyerhoff and Liebe, 2008,2010) would likely start seeking coastal plans other than status quo, and thus they are treated as non-participants.

6 Conclusion

This paper proposes a DHLC model to accommodate the presence and appearance of serial non-participation, particularly accommodating the potential heterogeneity in motives for this behavior in choice experiment studies. Motivated by a clustered preference pattern observed in pre-survey focus groups and the presence of serial non-participation in the final data set, this model strives to explain the clustered preference patterns and serial non-participation with individual attributes. Information criteria and the Vuong test show that the proposed DHLC approach fits the data significantly better than an unrestricted traditional LC model (but not necessarily better than a highly restricted one) while maintaining its advantages. Further analyses also hint that estimation biases potentially created by treating the non-participants as one latent class (in the LC models) can be nontrivial in characterizing the non-participation group and welfare analysis.

This study reveals three stable classes of Eastern Shore residents regarding coastal climate change adaptation plans: the pro-nature group taking care of the environment and land protection with little (apparent) regard for cost, the economy group paying much attention to cost, and the moderate environmentalist group considering tradeoffs across most attributes and expressing a relatively strong preference for management options involving living shorelines and favoring selected ecosystem services. Compared to the respondents, our results indicate that the general Eastern Shore population would have a higher proportion of non-participants and hence lower average WTP, which strengthens the relevance of the proposed econometric approach to addressing the non-participants. A projection to attain the population welfare measures suggests that, in general, the Eastern Shore residents' average willingness to pay for different coastal climate adaptation plans ranges from about 50 dollars to about 170 dollars per year for five years. Regarding the coastal plan attributes, we find that the alternative management plan (living shoreline) is preferred to the traditional seawall by the Eastern Shore residents who evaluated tradeoffs, and the ecosystem services bundled with the coastal plans have considerable but heterogeneous importance in Eastern Shore residents' considerations.

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