A Panel Travel Cost Model Accounting for Endogenous Stratification and Truncation: A Latent Class Approach

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Land Economics, Volume 89, Number 1, February 2013, pp. 177-192 (Article)

Published by University of Wisconsin Press

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ABSTRACT. *In this paper, we develop a panel data negative binomial count model that corrects for endogenous stratification and truncation. We also incorporate a latent class structure into our panel specification, which assumes that the observations are drawn from a finite number of segments, where the distributions differ in the intercept and the coefficients of the explanatory variables. The paper argues that count data panel models corrected for on-site sampling may still be inadequate and potentially misleading if the population of interest is heterogeneous with respect to the impact of the chosen explanatory variables.* (JEL Q51, Q57)

I. INTRODUCTION

The travel cost method (TCM) of nonmarket valuation, based on the count nature of recreation trips, can only measure values associated with the current use of a recreational site. However, an analyst, site manager, or policy maker may be more interested in the value to the user of potential changes to the facilities of a site or the value associated with some environmental change at the site. An extension to TCM surveys, therefore, has been to supplement the usual questions related to trips taken with one or more contingent behavior questions in which recreationalists are asked to state the number of trips they would take given either changes in site quality or changes in trip prices. This revealed and contingent response data can then be used in count data models to estimate the change in welfare associated with the change in the site or environmental attribute (Hanley, Bell, and Alvarez-Farizo 2003).

Combining revealed preference information and intended behavior responses involves obtaining multiple responses from the same individual. As such, an individual's multiple responses will likely be correlated due to individual specific but unobservable characteristic and taste parameters. Standard statistical count models fail to account for this correlation and are therefore inefficient.[1] Panel estimators such as fixed and random effects Poisson and negative binomial models have been previously employed to account for the possible correlation of multiple responses of the same individual (Greene 2008).

Endogenous stratification and truncation are two other important issues of relevance for contingent behavior models when the data has been collected on-site. Truncation refers to the fact that on-site data contains information on active visitors only and is therefore truncated at positive demand for trips to the site (Shaw 1988; Englin and Shonkwiler 1995). Secondly, an on-site survey is subject to the problem of endogenous stratification where due to the method of data collection the likelihood of being sampled depends on the frequency with which an individual visits the site. To date, few attempts have been made to account for these on-site sampling issues in panel data

[1] It has also been previously noted that estimates from TCM models that combine both stated and revealed trip information should result in more efficient parameter estimates, as more information on the same set of underlying preferences is employed in constructing the estimates (Hanley, Bell, and Alvarez-Farizo 2003).

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Land Economics • February 2013 • 89 (1): 177–192
ISSN 0023-7639; E-ISSN 1543-8325

count models. Researchers who have done so include Egan and Herriges (2006), Beaumais and Appéré (2010), and Moeltner and Shonkwiler (2010).

However, even the on-site-adjusted Poisson-based panel models used in these studies may be inadequate and potentially misleading if the recreational group of interest is heterogeneous with respect to the impact of explanatory variables. We account for this issue in this paper by extending a panel negative binomial model corrected for endogenous stratification and truncation to control for unobserved heterogeneity through the use of a latent class modeling framework that assumes that the observations are drawn from a finite number of segments, where the distributions differ in the intercept and the coefficients of the explanatory variables.

II. THE CONTINGENT BEHAVIOR MODELING APPROACH AND ACCOUNTING FOR ON-SITE SAMPLING IN PANEL DATA COUNT MODELS

There have been several attempts in the literature to combine the TCM revealed preference method and stated preference contingent valuation approaches to nonmarket valuation in the form of the contingent behavior model. This is done with the objective of measuring the welfare impact of a hypothetical change in implicit price or in environmental quality (Whitehead et al. 2008a). Examples of the use of the contingent behavior TCM approach in recreational demand modeling include studies by Englin and Cameron (1996), Grijalva et al. (2002), Hanley, Bell, and Alvarez-Farizo (2003), Christie, Hanley, and Hynes (2007), Martinez-Espineira and Amoako-Tuffour (2008), and Beaumais and Appéré (2010).[2]

While the majority of contingent behavior studies use panel rather than pooled count data specifications, other approaches have included panel data ordinary least squares models (Englin and Cameron 1996[3]), binary probit and random effects probit models (Loomis 1997), and panel tobit models (Azevedo, Herriges, and Kling 2003). What does stand out from the literature is the fact that the correction for endogenous stratification and truncation in contingent behavior models has, until very recently, been largely ignored. To avoid dealing with the issue of truncation in panel count data specification, many studies have discussed their per trip welfare estimates as being representative of their sample only and not of the general population of users (e.g., Hanley, Bell, and Alvarez-Farizo 2003; Starbuck et al. 2006; Christie, Hanley, and Hynes 2007).

The noncorrection of contingent behavior models based on on-site sampled data for endogenous stratification is even more prevalent in the literature than the nonadjustment for truncation. This may be due to the fact that there is no standard program available in statistical packages to deal with endogenous stratification in panel data count models and therefore some studies have simply pooled the revealed and contingent observation points and run endogenously stratified truncated Poisson or negative binomial models, which are routinely available. For example Starbuck, Berrens, and McKee (2006) employed a pooled endogenously stratified truncated Poisson model to estimate consumer surplus and predict changes in recreation visits to a forest site under three alternative management scenarios. This pooling technique ignores the fact that there is likely to be substantial correlation between the revealed and contingent behavior responses from the same individual.

It is also worth noting that a simple adjustment used to correct for endogenous stratification in the univariate Poisson model is to transform the dependent variable, Y_i (number of trips taken by individual i), to equal Y_{i-1} (this adjustment is possible assuming a univariate Poisson distribution for the dependent

[2] For an in-depth review of the contingent behavior modeling literature, the interested reader should see Whitehead et al. (2008b).

[3] Englin and Cameron (1996) also applied a fixed effects Poisson model to compare to the fixed effects ordinary least squares model and to test for differences in price elasticities and consumer surplus from separate demand equations estimated with observed number of trips and intended number of trips for three hypothetical cost increases.

variable and Shaw's [1988] derived on-site sampling distribution). Hesseln, Loomis, and González-Cabánc (2004) use this adjustment technique in a pooled contingent behavior model that examines the effects of fire on hiking demand in Montana and Colorado. However, as Egan and Herriges (2006) point out, the above technique applies only to the univariate setting, and this simple adjustment is not appropriate with the use of the panel data specification.

Others have used strategies that avoid the need to account for endogenous stratification at all in a TCM framework by intercepting visitors away from the study site, either using club member registers to target the relevant respondents for a site (Scarpa, Thiene, and Tempesta 2007) or intercepting recreationalists close to the study site (Mendes and Proença 2009). In these cases, a zero-inflated travel cost model is employed where the zero trip observations are assumed to be generated from one of two processes. The model takes into account that some respondents derive zero utility from the recreational activity (trip outcomes are always zero and not generated by the Poisson process), while others are in the market for the recreational activity but optimally choose zero trips to the study site (the usual Poisson process applies, and the zeros represent the individual's utility maximizing recreation decision).[4] Elsewhere, Hynes and Hanley (2006) avoid the need of adjusting their truncated negative binomial TCM for endogenous stratification by combining data from their on-site survey with a non-site-based survey—in their case, survey data collected via the Internet. In this manner the sample incorporates individuals who visit the recreational site but who have a lower probability of being sampled on-site due to less frequent visits.

It has also been suggested that the issue of endogenous stratification can be dealt with in a panel data count specification by simply applying a sampling weight to observations equal to the inverse of the estimated probability that an individual will visit the site. This reduces the proportional influence on the estimated model of individuals that have a higher probability of being included in the sample because of the on-site sampling design (i.e., those who are more likely to be sampled due to the increased frequency with which they visit the recreational site). Wooldridge (2002) demonstrates how this inverse probability weighting recovers the population moments from a selected sample.

As mentioned in Section I, only three papers to date have produced a panel data count model that explicitly corrects for both truncation and endogenous stratification. These are by Egan and Herriges (2006), Beaumais and Appéré (2010), and Moeltner and Shonkwiler (2010). In the case of Egan and Herriges (2006), the authors develop a multivariate Poisson log-normal model to jointly model revealed and contingent behavior data and to correct for on-site sampling. They also estimate Winkelmann's (2000) seemingly unrelated negative binomial model, also adjusted for truncation and endogenous stratification. The authors conclude that there is substantial bias in the results if the sampling procedures are ignored, overstating both the average number of trips to the site (by a factor of 14) and the welfare associated with the recreational opportunities at study site.

Beaumais and Appéré (2010) extend the work of Egan and Herriges (2006) by addressing the on-site sampling issue within the framework of a random-effect Poisson gamma model.[5] Their modeling approach constrains the correlation across counts for the same panel to be positive. This is not a priori the case of

[4] For further discussion on the use of methods that intercept respondents away from the study site but ask about frequency of visits to that site (and the use of associated zero-inflated trip demand models), the interested reader should see Shaw and Jakus (1996) and Martinez-Espineira (2007) for further discussion.

[5] Beaumais and Appéré (2010) also introduce the concept of a "twin site." In their surveying approach they introduce to the respondent the hypothetical existence of a site strictly identical to the study site with a difference only in the environmental quality of certain attribute and try and establish the maximum distance the respondents would be willing to travel to such an alternative site and the number of extra trips if any that individuals would make to such a site. This approach to defining the hypothetical scenario in a contingent behavior study differs from that usually found in the literature, where the change in environmental condition is defined in terms of the study site itself.

Egan and Herriges's (2006) multivariate Poisson log-normal specification. Similar to Egan and Herriges, Beaumais and Appéré (2010) and Moeltner and Shonkwiler (2010) also find that correcting for on-site sampling has a significant impact on model parameters and the consumer surplus estimates.

Finally, it should be noted that count data panel models that incorporate unobserved heterogeneity, with respect to the impact of the explanatory variables have also been previously developed. For example, Wang, Cockburn, and Puterman (1998), in the analysis of patent data, developed Poisson regression models for count data that accommodated heterogeneity arising from a distribution of both the intercept and the coefficients of the explanatory variables. The study assumed that the mixing distribution was discrete, resulting in a finite mixture model formulation. There have also been other papers using latent class approaches in count travel cost models. Scarpa, Thiene, and Tempesta (2007), for example, examined the existence of latent classes in the total demand for recreational days in the eastern Italian Alps by applying finite mixing to a zero-inflated cross-sectional count demand model. Elsewhere, Baerenklau (2010) also used a latent class approach to incorporate unobserved heterogeneity into an aggregate count data framework in an effort to control for endogenous spatial sorting in zonal recreation models. Advances in computational capabilities have also meant that statistical packages such as Nlogit (Greene 2007) now contain standard commands that allow the researcher to readily incorporate a discrete mixture distribution into panel count models.

As is evident from the previous (nonexhaustive) review of the literature, much has been written in terms of the issues surrounding on-site sampling issues related to the TCM. To date, however, no count data model exists for panel data that simultaneously accounts for the on-site sampling issues of endogenous stratification and truncation and the presence of unobserved heterogeneity via slope coefficients for the explanatory variables. The specification of such a model is presented in the following section. In particular, we develop a random effects panel data model with a latent class framework that also accounts for truncation and endogenous stratification.

III. METHODOLOGY

In our study of recreational demand at Silverstrand Beach, Ireland, the variables of interest are a count of beach trip demand in the previous 12 months and a count of potential beach trip demand that the same individuals would make given some hypothetical change in site quality or facilities. In effect, each person i in the data set yields two responses. The first is the number of trips (y_{i1}) the person makes to the beach under current conditions (response or scenario $t = 1$), and the second observation is how many trips (y_{i2}) the person says he or she would make if a specified improvement in recreational facilities at the beach occurs under hypothetical conditions (response or scenario $t = 2$). These counts are limited to nonnegative integers. In the contingent behavior modeling framework, we require a panel data modeling approach. The distribution of data on beach trip recreation is also positively skewed toward zero, thus preventing the use of a standard ordinary linear regression model.

Following the work of Shaw (1988), Grogger and Carson (1991), Englin and Shonkwiler (1995), and Greene (2008) we assume that, based on such data, a panel data count model of recreational demand can be estimated using a negative binomial distribution for the dependent count variable. As with Englin and Shonkwiler (1995) we also need to adjust our modeling strategy to control for the fact that our data were collected on site. Unique in the literature, we also adjust our random effects panel data negative binomial model corrected for on-site sampling to allow for the mixing of taste intensities over a finite group of taste segments in the population. Unobserved heterogeneity in the distribution of y_{it} is assumed to impact the mean (and variance) λ_{it}. The continuous distribution of the heterogeneity is approximated using what Greene (2008) refers to as a finite number of "points of support." The distribution is approximated by estimating the location of the support points and the mass probability in each interval. We interpret this discrete approximation as producing a sorting of individuals into C classes, $c = 1, \ldots, C$. Therefore, in what follows we modify our random effects panel data negative binomial model corrected for on-site sampling for a latent sorting of y_{it} into C classes.

Our starting point for a panel of trip data, $I = 1, \ldots, N$ individuals and $t = 1, \ldots, T_i$ responses (here, $T_i = 2$) for that individual, is the standard negative binomial model for count data that allows for overdispersion in the responses:

$$P(y|\mathbf{x}) = \frac{\Gamma(y+1/\alpha)}{\Gamma(1/\alpha)\Gamma(y+1)}\left(\frac{1/\alpha}{\lambda+1/\alpha}\right)^{1/\alpha}\left(\frac{\lambda}{\lambda+1/\alpha}\right)^{y}, \quad [1]$$

where $\lambda = \exp(\boldsymbol{\beta}'\mathbf{x})$ is the conditional mean function and $1/\alpha$ is the overdispersion parameter (for convenience at this point, observation subscripts are omitted). The vector $\mathbf{x}$ represents the set of explanatory variables reported for each individual i. It is a $k \times 1$ vector of observed covariates, and $\boldsymbol{\beta}$ is a $k \times 1$ vector of unknown slope parameters. The scalar α and the vector $\boldsymbol{\beta}$ are parameters to be estimated from the observed sample. Finally α is a structural parameter to be estimated along with $\boldsymbol{\beta}$. Larger values of α correspond to greater amounts of overdispersion. The model reduces to the Poisson when $\alpha = 0$.

The density that applies to the observations obtained on site was shown by Shaw (1988) to equal

$$P(y|\mathbf{x},\ on\ site) = \frac{yP(y|\mathbf{x})}{\sum_{s=1}^{\infty} P(s|\mathbf{x})}. \quad [2]$$

For the negative binomial model in particular, the result (see Englin and Shonkwiler 1995, 106, [9]) is

$$P(y|\mathbf{x},\ on\ site) = \frac{y\Gamma(y+1/\alpha)\alpha^{y}\lambda^{y-1}(1+\alpha y)^{-(y+1/\alpha)}}{\Gamma(1/\alpha)\Gamma(y+1)}, \quad y = 1,2,\ldots. \quad [3]$$

The second extension in our model is the accommodation of the latent sorting of individuals into C groups, or classes. The analyst does not observe directly which class, $c = 1, \ldots, C$, generated observation $y_{it}|c$, and class membership must be estimated. The latent class model, in generic form, conditioned on the particular class can therefore be written as

$$P(y|\mathbf{x},\ on\ site,\ class = c) = F(y|\mathbf{x}, \boldsymbol{\beta}_c, \alpha_c). \quad [4]$$

It should be noted that there is a separate dispersion parameter in each class as well. The unconditional *prior* probabilities attached to the latent classes are given by

$$\pi_c = \text{Prob}(class = c) = \frac{\exp(\tau_c)}{\sum_{q=1}^{C}\exp(\tau_q)}. \quad [5]$$

The logit formulation for the probabilities is a convenient parameterization that allows the prior class probabilities to be constrained to the unit interval and to sum to one. The normalization $\tau_C = 0$ is imposed because only $C - 1$ parameters are needed, with the adding up restriction, to specify the C probabilities. With this structure, there is a one to one correspondence between the set of parameters $(\tau_1, \ldots, \tau_{C-1}, 0)$ and the set of class probabilities $(\pi_1, \ldots, \pi_{C-1}, 1 - \sum_{c=1}^{C=1}\pi_c)$. For an individual observation, the unconditional probability is averaged over the classes,

$$P(y|\mathbf{x},\ on\ site) = \sum_{c=1}^{C} \pi_c P(y|\mathbf{x},\ on\ site,\ class = c). \quad [6]$$

The probability $P(y|\mathbf{x}, \textit{on site})$ is the term that enters the log likelihood that is maximized to obtain the estimates of $\boldsymbol{\theta} = [(\beta_1, \alpha_1), (\beta_2, \alpha_2), \ldots, (\boldsymbol{\beta}_C, \alpha_C), (\tau_1, \ldots, \tau_C)]$. The log likelihood for the observed sample is, therefore,

$$\log L = \sum_{i=1}^{N} \log\left\{\sum_{c=1}^{C} \pi_c P(y_i|\mathbf{x}_i, (\boldsymbol{\beta}_c, \alpha_c),\ on\ site,\ class = c)\right\}, \quad [7]$$

where π_c is given in [5] and $P(y_i|\mathbf{x}_i, (\boldsymbol{\beta}_c, \alpha_c)$ on site, class $= c)$ is given in [3] with $\lambda_i = \exp(\boldsymbol{\beta}_c{}'\mathbf{x}_i)$.

Individuals are observed more than once in the sample. We make the usual assumption that conditional on the class membership, which does not change for the person, the trip choices are made independently. There is correlation induced across choices in that the observed variables, $\mathbf{x}_i$, are correlated across visits and, as well, since the class membership is fixed, the individuals' preferences, embodied in $\boldsymbol{\beta}_c$, are also common across visits. However, we have not assumed that there are unobserved factors that are omitted from the model and that are correlated across visits. With these assumptions, the joint probability of the T_i trip choices by individual i is given by

$$P(y_{i1},\ldots,y_{iT_i}|\mathbf{x}_{i1},\ldots,\mathbf{x}_{iT_i},\boldsymbol{\beta}_c,\alpha_c,\ \textit{on site, class} = c) = \prod_{t=1}^{T_i} P(y_{it}|\mathbf{x}_{it},\boldsymbol{\beta}_c,\alpha_c,\ \textit{on site, class} = c). \quad [8]$$

The log-likelihood for the panel of data is obtained by inserting the joint probability in [8] in the log-likelihood in [7]:

$$\log L = \sum_{i=1}^{N} \log\left\{\sum_{c=1}^{C} \pi_c \prod_{t=1}^{T_i} P(y_{it}|\mathbf{x}_{it},\boldsymbol{\beta}_c,\alpha_c,\ \textit{on site, class} = c)\right\}. \quad [9]$$

The function in [9] is maximized with respect to $\boldsymbol{\theta} = [(\beta_1,\alpha_1),(\beta_2,\alpha_2),\ldots,(\boldsymbol{\beta}_C,\alpha_C),(\tau_1,\ldots,\tau_C)]$.

Finally, it should be noted that the approach of adjusting for truncation and endogenous stratification in both the observed and contingent observations distribution is different from that of Egan and Herriges (2006) and Beaumais and Appéré (2010) where the observed behavior data are assumed truncated to zero and endogenously stratified but the contingent behavior data are not. Thus the on-site sampling correction is specified only through observed data in their case. Even though our second observation for each person is the hypothetical number of trips that person would make under changed site conditions, we argue that the problem of endogenous stratification and truncation still holds. The respondent is still someone who has a higher likelihood of being included in the sample due to his or her frequency of use. Also, given that the contingent behavior question is commonly set up such that respondents are asked how many more trips (if any) they would make to the site given an improvement in facilities (and therefore y_2 cannot be less than y_1), truncation still exists in the second period, as we are still dealing only with individuals who will use the facility at least once.[6]

For consumer utility maximization subject to an income constraint, and where the number of trips are a nonnegative integer, Hellerstein and Mendelsohn (1993) show that the expected value of consumer surplus, $E(CS_{it})$ derived from count models, can be calculated as $E(CS_{it}) = E(y_{it}|x_i)/\beta_{pi} = \hat{\lambda}_{it}/(\beta_{pi})$, where y_{it} is the number of trips to the beach for individual i under conditions t, and λ_{it} is the underlying rate at which the number of trips occur, such that one would expect some number of trips in a particular year, in other words, λ_{it} is the mean of the random variable Y_{it}. The coefficient, β_{pi} is the individual price (*i.e.,* travel cost) coefficient. The per-trip $E(CS_{it})$ is simply equal to $-1/\beta_{pi}$. The change in the consumer surplus resulting from an improvement in the coastal amenities is then given by

$$\Delta E(CS_i) = \Delta E(y_{ij}|x_i)/\beta_{pi} = (\hat{\lambda}_i^* - \hat{\lambda}_i)/\beta_{pi}, \quad [10]$$

where $\hat{\lambda}_i$ is the expected number of trips before any improvements are made to the coastal amenities ($t = 1$) and $\hat{\lambda}_i^*$ is the expected number of trips after improvements are made to the coastal amenities ($t = 2$). This suggests that the change in consumer surplus for individual i can be calculated by dividing the change in the predicted number of trips to the beach site by the coefficient of the travel cost variable. It is important to state that the relevant comparison in welfare terms is between the number of predicted trips at the current level of coastal amenity provision at the beach site and the predicted number of trips at the improved level. Also, it should be noted that

[6] Interestingly, Moeltner and Shonkwiler (2010) showed that on-site sampling issues persist even for past season trip reports if the respondent is intercepted on site this season. The authors labeled this effect "avidity carryover." They found that for their sample of lake visitors, relatively stronger preference or "avidity" for the interview site carries over across seasons. We argue that a similar effect could apply to hypothetical trip reports, if we interpret them as "future season trips." If that is indeed the case then this again implies that the contingent behavior data as well as the observed behavior data should be assumed truncated.

one cannot disaggregate benefit estimates into additional utility from those who take no extra trips to the beach and additional utility from those who visit most frequently. The beach travel cost study and the on-site collected data set employed are described in the next section, prior to the presentation of model results and welfare estimates.

IV. DATA AND STUDY BACKGROUND

The application of our model is to a data set generated from a survey that examined the possible welfare impact associated with the development of a coastal trail that connects two beach areas along the Galway Bay coastline in the west of Ireland. The data was generated from an on-site survey of visitors to Silverstrand beach, approximately 7 km outside of Galway city, which is accessible by public road only. The beach itself is only 300 m long and has only limited facilities in the form of parking, benches, picnic tables, and toilet facilities. Nevertheless it is a popular destination, particularly in the summer months for outdoor enthusiasts, and is used heavily by the local urban community of Galway city and surrounding area as a recreational amenity. The beach was of interest as it is a site where potential exists to add recreational value through the establishment of a walking trail that would link it to another area of beach currently cut off by a small area of farmland.

Failte Ireland (2008) reported that holidaymakers do not visit Ireland for the typical beach holiday, but rather seek out soft adventure activities such as walking, kayaking, and so on along the coast. It has also been noted that one of the best means for improving the value of coastal resources such as beaches is through the provision of walking trails. These not only provide a valuable source of recreation to the public but also provide increased access to the coastline. However, some of the best coastal walking areas in Ireland can be accessed only through private farmland, and under Irish law, access to privately owned land for the purpose of recreation is at the discretion of the landowner. A variety of issues such as potential interference with agricultural activities, insurance liability, and potential invasion of privacy have been cited by landowners as reasons why they may be unwilling to permit public access to their farmland for walking-related activities (Buckley et al. 2009).

Silverstrand beach was chosen as a site to investigate the issue of coastal access. Next to the beach is a strip of privately owned agricultural land that has a cliff face at the water's edge. The strip of agricultural land prevents the access by recreationalists to a much larger area of beach and also prevents access along the shore to the nearby Salthill Beach and promenade. If recreationists could freely cross this section of agricultural land, it would open up a coastal walk of over 4 miles. At present, users of Silverstrand have no right to cross the private farmland to access the additional beach area. With this in mind, respondents were asked a contingent behavior question in relation to how their usage of the beach facility would change if the length of beach at their disposal was increased through the opening up of a cliff walk that would give them access to an additional 1 km of beach and also access along the shore to Salthill Beach and the promenade. The features of the new walking trail were pointed out to respondents on a map, as well as information on how the new walking trail would also open up access to the nearby Salthill Beach.

As part of the study, 146 personal interviews were carried out at the beach site. The questionnaire was piloted over a two-week period in June 2009. This was followed by the main survey, which took place at Silverstrand during the months of July and August 2009. Due to the nonresponse to certain questions in the main survey, 18 surveys were not deemed usable in the final analysis, which resulted in a final sample of 128 individual responses being used for model estimation. The on-site interviews were conducted on both week days and weekends, during all daylight hours. The questionnaire solicited information on trips taken to the beach, activities undertaken, personal demographics, income, employment status, education, social relations, and obligation-free time. Each interview took approximately 20 minutes.

Respondents were provided with background information on the study and were then asked to outline how they used the beach for recreation. Next, they were presented with

Suppose that NEXT YEAR a new WALKING PATH was built connecting to this beach resource.

The path would consist of:

- An approx 2 km round trip walk along the cliffs to the end of the spit at Rusheen Bay.
- Walkers would be granted formal right of way along the walk (currently people walk along the cliff but are not supposed to as it is privately owned farm land).
- A marked path with a fence to separate the walk from the farm land and cliff edge.
- Informational plaques detailing the surrounding countryside.

All facilities would be built with material that blends in with the coastal amenity.

How would these new facilities affect your use of THIS BEACH?

FIGURE 1
Scenario Examined in Contingent Behavior Study

information on how the beach (where they were sampled) might be improved for recreation. Respondents were then presented with the contingent behavior scenario (as shown in Figure 1) and asked if the site changes described on the card were implemented at the beach resource, would they change the number of trips they would take to the site over the next 12 months. This was followed up with an option of choosing (1) no change in number of trips taken, (2) more trips, or (3) fewer trips. Finally, the respondent was asked to state the increased (or decreased) number of trips if they had chosen option 2 (or 3).[7] Thus, two observations for trips taken were collected from each respondent: the actual number of trips taken in the previous 12 months and the contingent number of trips that would be taken if the walking trail was put in place. This resulted in a panel data set of 256 observations. Finally, attitudinal data was also collected from the respondents.

Each respondent's travel cost was computed following the standard approach in the literature by considering the direct costs and the opportunity cost of travel. For each respondent i and each scenario t, the travel cost was calculated as

$$TC_{it} = \left(\frac{Dist_{it} \times CostperKM}{Groupsize_i}\right) + \left\{Time\left[0.25 \times \left(\frac{Income_i}{2000}\right)\right]\right\},$$

where $Dist_{it}$ is the round-trip distance from the respondent's home to the site, *Time* is the return travel time (in hours) from home to site, *CostperKM* is the average petrol cost per mile,[8] and $Groupsize_i$ is the number of people that traveled to the site in the respondent's vehicle. Following Shaw and Feather (1999), the opportunity cost of travel time is included in the travel cost calculation as a proportion (0.25) of the hourly wage, where the hourly wage rate was taken as the respondents reported income divided by 2,000, based on a 40 hour week for 50 weeks in a year. No allowance for on-site time was made in the travel cost calculation.[9]

Relaxing/sun bathing was highlighted as the main activity of 35% of all respondents in the survey followed by entertaining children (21%), swimming (13%), walking (11%), and other water sports (6%). Also, it is notable that 49% of respondents were male, 57% were in full-time employment, and 63% had been educated up to degree level. Mean annual visits to the beach where each respondent was sampled were 11.76 (range 1 to 60). The day of the survey was the first ever visit to the beach for 7% of the sample, and respondents spend on average 2 hours 31 minutes on site. A visit to the beach was the main purpose of the day's journey for 61% of the sample, and participants in the survey used the beach resource for, on average, 4.1 different recrea-

[7] As is often the case in contingent behavior studies of this type, no respondent chose option number 3.

[8] The Automobile Association of Ireland's calculation of €0.224/mile, obtained from www.aaireland.ie/infodesk/cost_of_motoring.asp, was used.

[9] An in-depth discussion of the many issues that surround the calculation of the travel cost variable is beyond the scope of the article, but for a good overview of the treatment of time and the specification of the travel cost variable in recreation demand models, the interested reader is advised to see Shaw and Feather (1999) and Hynes, Hanley, and O'Donoghue (2009).

TABLE 1
Summary Statistics

Variable Name	Description	Mean	Std. Dev.
Actual trips	Number of trips respondent actually took to the beach in last 12 months	11.76	14.9
Hypothetical trips	Number of trips respondent would take in next 12 months if scenario implemented	17.31	19.23
Age	Age	41.06	13.68
Income	Gross annual income (€)	51,551	29,334
Incidental visit to beach	Dummy indicating whether trip to beach occurred by chance as happened to be in the area anyway (1) or was a planned trip to the beach (0)	0.39	0.49
Member of recreation or environmental organization	Dummy variable indicating whether the respondent is an active member of a recreational organization such as a kayak or surf club or an environmental organization such as Birdwatch Ireland or Greenpeace	0.47	0.5
Travel cost	Return travel cost from home to beach	15.28	17.43
Travel cost substitute site	Return travel cost to the alternative site most frequently visited by respondent	13.77	15.32
Water sport participation	Dummy variable indicating whether trip to beach involved a water sport	0.15	0.36

tional activities. Mean one-way distance traveled was 24 miles, and respondents to the survey tended to be at the beach in groups of, on average, 2.2 persons (range 1 to 13). Further summary statistics associated with the sample are presented in Table 1.

V. RESULTS

Given the contingent behavior scenarios described in Figure 1 and the model specifications described in Section III, we present here the results of two panel models. Table 2 presents the results of both a random effects negative binomial model corrected for on-site sampling and a random effects latent class negative binomial panel model also corrected for endogenous stratification and truncation. Although not discussed here in detail, both pooled versions of the Poisson and negative binomial model were also initially fitted, as were random effects Poisson and negative binomial models uncorrected for on-site sampling.[10] The results for these models are presented in the Appendix, and for the purpose of comparison we also estimate and present the mean consumer surplus per trip estimates and the change in consumer per trip estimates as a result of the new coastal walking trail for all models in Table 3.

In all models, the average number of trips undertaken by individual i under (the real or contingent) scenario t is assumed to be a function of the travel cost to the site, the travel cost to the respondent's next preferred substitute site, whether the respondent participates in a water sport while on-site, is a member of a recreational or environmental organization, income, age, whether the visit to the beach is simply due to the respondent being in the area for other business and a "contingent behavior" variable, which indicates whether the visits we are explaining are actual, with current facilities, or hypothetical, with improved facilities. A further description of each of the independent variables is given in Table 1.

The model in the first column of Table 2 is the random effects panel negative binomial accounting for on-site sampling (henceforth referred to as the NB corrected model) while the second and third columns present the results of the negative binomial panel model that allows for unobserved heterogeneous with respect to the impact of explanatory variables on the number of trips taken as well as accounting for the issue of on-site sampling

[10] Whether a panel specification was preferred to a pooled specification was tested, and the likelihood ratio test statistic confirmed the need for a panel rather than a pooled regression.

TABLE 2
Negative Binomial Contingent Behavior Models Accounting for Truncation and Endogenous Stratification

	Negative Binomial Panel Count Model	Latent Class Negative Binomial Panel Count Model	
		Latent Class 1	Latent Class 2
Age	0.156*** (0.035)	0.104*** (0.031)	0.215*** (0.052)
Income	− 0.003 (0.002)	− 0.005** (0.002)	0.003 (0.002)
Incidental visit to beach	− 1.202*** (0.145)	− 1.481*** (0.197)	− 0.680*** (0.221)
Member of recreation or environmental organization	0.404*** (0.094)	− 0.052 (0.101)	0.180 (0.114)
Contingent behavior	0.481(0.388)	0.292* (0.172)	0.666*** (0.210)
Travel cost	− 0.033*** (0.009)	− 0.047** (0.019)	− 0.064*** (0.017)
Travel cost substitute site	0.032*** (0.009)	0.067*** (0.022)	0.039** (0.016)
Water sport participation	0.553*** (0.145)	0.166 (0.155)	0.437** (0.182)
Constant	0.463 (0.420)	3.529*** (0.184)	0.534* (0.280)
Scale parameter/alpha in LC	1.345 (1.584)	0.051** (0.026)	0.722*** (0.176)
Class probabilities		0.217*** (0.040)	0.783*** (0.040)
AIC	1,735	1,605	
BIC	1,771	1,679	
Log likelihood	− 858	− 781	

Note: Standard errors are in parentheses. The income variable has been rescaled by dividing by 1,000.
* Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

TABLE 3
Consumer Surplus (CS) and Change in Trips Taken Estimates from Alternative Model Specifications

Model Specification	Mean CS per Trip (€)	Change in Number of Trips Taken as Result of New Walking Trail	Change in CS as Result of New Walking Trail (€)
Pooled Poisson[a]	59.35 (43.09, 75.60)	5.63	334.23
Pooled negative binomial[a]	125.02 (− 38.15, 288.20)	6.19	774.12
Basic panel Poisson	35.88 (15.09, 56.66)	3.51	125.94
Basic panel negative binomial	34.64 (1.31, 67.97)	4.87	168.56
Panel Models Accounting for Truncation and Endogenous Stratification			
Negative Binomial	30.54 (14.11, 46.96)	3.32	101.44
LC negative binomial: Class 1	21.43 (4.20, 38.65)	6.04	129.39
LC negative binomial: Class 2	15.67 (7.36, 23.98)	6.04	94.61
Weighted LC negative binomial[b]	16.93 (6.66, 27.21)	6.04	102.26

Note: All values are per person. Ninety five percent confidence interval in parentheses.
[a] The model results of the pooled Poisson and pooled negative binomial models are not presented in this paper but are available from the authors upon request.
[b] This is the weighted CS per trip estimate estimated by considering the class probabilities in the NB latent class model.

(henceforth referred to as the LC corrected NB model). The travel cost coefficients in both models are significant at the 5% level and have the expected negative signs. This indicates that, on average, as the cost of traveling to the beach site decreases, the number of trips made to the site increases. The "travel cost to the nearest substitute site" and the "incidental visit to the beach" variables are also significant and have the a piori expected signs.

The one major difference between both models in terms of the estimated coefficients is that the contingent behavior variable is insignificant in the NB corrected model. This finding would appear to suggest that the hypothetical trail that facilitates access to a further area of beach does not have a statistically significant effect on the number of planned trips to the site. Once we account for the unobserved heterogeneity in our sample, however, the contingent behavior variable in our LC corrected NB model is significant (at the 90% level in Class 1 and at the 99% level in Class 2). In fact, all variables bar being a member of a recreation or environmental group are now significant at the 95% level in at least one of the two class segments.

With respect to the definition and testing of hypothesis on the number of classes to include in the latent class corrected NB model, the conventional specification tests used for maximum likelihood estimates are not valid as they do not satisfy the regularity conditions for a limiting chi-square distribution under the null (Hynes et al. 2008). Therefore, in order to decide the number of classes, we used the information criteria statistics first developed by Hurvich and Tsai (1989). We report the Akaike information criterion (AIC), the Baysian information criterion (BIC), and the Hannan Quinn statistic for all models in Table 2 and Appendix Table A1. In terms of the latent class corrected NB model, no one number of classes minimizes each of the measures. The three-class specification has the lowest score on two of the criteria, while the two-class specification is lowest for the BIC. As Scarpa and Thiene (2005) point out, these statistics provide guidance on the number of latent classes to choose, but this decision also requires the discretion of the researcher. We hence choose to report in Table 2 only the LC corrected NB model estimates for the two-class model even though two of the information criteria statistic were lower for the three- and four-class models. We reject the four-class model as one of its classes has a complete set of insignificant parameter estimates and also both the three- and four-class models displayed a high number of insignificant parameter estimates in at least one of their other classes.

As can be seen from Table 2, the two-class model specification allocated 22% of respondents to Class 1 and 78% to Class 2. Importantly, the travel cost coefficients in both classes are negative and significant at the 5% level, and, as mentioned above, the contingent behavior variable is also significant in both classes. It is also interesting to note that the income coefficient is now significant for the smaller group of recreationists likely to be represented by Class 1. This coefficient was insignificant in all earlier versions of the contingent behavior model. Only by allowing for taste heterogeneity in the sample do we pick up on the importance of this characteristic for a certain portion of recreationalists using the site. It should also be noted that for this smaller segment, participation in water sports has no influence on the number of trips made to the site, whereas it has for Class 2. The travel cost variable would appear to have more or less the same influence on both, which would suggest that both classes exhibit price sensitivity to the same degree.

Finally, it should be noted that that the LC corrected NB model had a lower log-likelihood value (in absolute terms) and a lower score on all of the information criteria statistics than the NB corrected model, indicating that the latent class structure provides a better fit for our on-site sampled data than when we assume a homogenous mean influence of the explanatory variables among our beach recreationists.

Following Beaumais and Appéré (2010) we also carried out a Vuong test (Vuong 1989) to examine if the on-site sampling correction to the negative binomial specification was appropriate. Previously Greene (1994) adapted the Vuong test to examine the appropriateness of a zero-inflated negative binomial versus a standard negative binomial model. The Vuong statistic has a limiting distribution that is normal with large positive values favoring the corrected model and with large negative values favoring the standard panel version of the negative binomial model unadjusted to account for on-site sampling. Values close to zero in absolute terms favor neither model. The calculated Vuong statistic of 9.54 results in a clear rejection of the null hypothesis that not accounting for on-site sampling has no effect on the means or the variances in the negative binomial panel specification of the contingent behavior model (i.e., that the models are indistinguishable).

Estimating the welfare effects of changes in the quality or supply of site facilities or environmental goods is the main objective of most contingent behavior studies. We therefore consider the implications for welfare measures of controlling for on-site sampling and unobserved heterogeneity. In particular we compare the consumer surplus (CS) per trip (real behavior), the estimates of the change in number of trips taken, and the change in total CS per recreationalist as a result of the hypothetical extension to the beach being provided through the creation of an adjoining walking trail, across the alternative model specifications. Table 3 also reports the estimates for the basic (unadjusted for on-site sampling issues) pooled and panel Poisson and negative binomial specifications.

The panel negative binomial models accounting for truncation and endogenous stratification result in lower mean CS estimates and lower predicted trips taken than the basic pooled and panel Poisson and NB models. The distribution of CS estimates for the LC corrected NB model varies across classes, with each class having a specific CS per trip estimate. The class-weighted population estimate of per trip consumer surplus for the latent class corrected NB model is estimated with 95% confidence to be between €16.93 and €27.21. With a mean CS per revealed trip estimate of €21.67 and €15.67 for Class 1 and 2, respectively, this model provides the most conservative mean CS estimates across all the reported models.

While nothing in the construction of the LC corrected model assures that the CS measures in a two-class model will bracket the result from a one-class model (the NB corrected model), it is still interesting to note that the CS estimate in the NB corrected model does not fall between the two-class estimates of the latent class corrected NB model. This may be an indication that the one-class model is forcing an overestimate of the consumer surplus measure and that controlling for heterogeneity in the population with respect to the impact of the chosen explanatory variables provides more reliable CS estimates.

To estimate the recreation benefits from the access improvements and the addition of the walking trail and additional beach area, the steps outlined in the methodology section were followed. To calculate the proportional change in recreationalist welfare from implementation of the coastal walking trail, we first take into account the stated change in trips to the beach site if the trail were to be put in place. Such a facility improvement would increase visits by an estimated 3.32 trips per year under the NB corrected model. This is the lowest predicted change in trips across all model specifications.

Even though the LC corrected NB model provides the lowest mean CS per trip estimates, it predicts the second-largest change in the number of trips taken per individual as a result of the beach site changes being implemented (6.04 additional trips per person per year). However, the relatively low CS per trip estimate for the LC corrected NB model means that the estimated total increase in consumer surplus from the beach facility improvements per person per year (the class-weighted estimate) is only €0.82 higher than the estimate associated with the NB corrected model (€102.26 and €101.44, respectively). The panel negative binomial model that does not account for truncation and endogenous stratification produces estimates for the change in CS per person per year that are approximately 65% larger than those of the models that do account for on-site sampling, while the pooled unadjusted models (which is still an approach used in the literature; see, e.g., Hesseln, Loomis, and González-Cabánc 2004) provide estimates that are over 300% higher.

VI. DISCUSSION AND CONCLUSIONS

In this paper, we presented an extension to Shaw's (1988) and Englin and Shonkwiler's (1995) count data models corrected for on-site sampling to a panel data setting. We contrasted a panel negative binomial model that accounted for the fact that the sample was collected on site with a latent class random effects panel data negative binomial model corrected for on-site sampling but at the same time allowing for the mixing of taste intensities over a finite group of taste segments in the population. The chosen models were applied to revealed and contingent travel data obtained from a survey of visitors to a beach on the outskirts of Galway city in Ireland.

While Egan and Herriges (2006), Beaumais and Appéré (2010), and Moeltner and Shonkwiler (2010) have previously developed count data panel models corrected for on-site sampling, their approaches may still be inadequate and potentially misleading if the population of interest is heterogeneous with respect to the impact of the chosen explanatory variables. The error term added to the parameterized mean function of the Poisson models used by the aforementioned authors can be interpreted as capturing unobserved heterogeneity. However, what was still missing in the literature up until this paper was an on-site corrected count data model that captures unobserved heterogeneity via slope coefficients for explanatory variables. Our proposed methodology accounts for heterogeneity in both the underlying mean number of trips taken and the regression coefficients. That is, our model assumes that the observations are drawn from a finite number of segments, where the distributions differ in the intercept and the coefficients of the explanatory variables. Within each class the population interest is homogenous with respect to the impact of explanatory variables, but this assumption is relaxed across classes.

We contend that the use of latent class modeling approach is particularly relevant for on-site sampled recreationalists. Users of a recreational site such as a beach or a forest park tend to be diverse and have different reasons for wanting to visit such sites. In the discrete choice recreational demand literature, this has been a well recognized fact since Train (1998), and now the publication of almost all work involving the estimation of destination choice random utility models involves modeling the site choice decision for recreationists allowing for the mixing of taste intensities either over a finite group of taste segments (the latent class approach) or over continuous value distributions (random parameter logit approach).[11] Barring some notable exceptions such as those of Scarpa, Thiene, and Tempesta (2007) and Baerenklau (2010), this recognized heterogeneity across recreational groups using a site such as a beach (and indeed even within particular recreational groups) has not been given the same treatment in count data travel cost models of recreation demand (and never in the case of travel cost models adjusted for on-site samples) as it has in the discrete choice literature. This paper fills that gap in the literature.

The LC corrected NB model facilitated a much deeper analysis of the factors driving the decision to make a particular number of trips to the beach site. It also highlighted the fact that there are distinct segments of the population who make that decision based on different influences. For instance, in one segment, having a higher income has a significant (and negative) influence on the number of trips taken while participating in a water sport at the beach site did not. In the second segment, income had no significant influence while participating in a water sport at the beach site was highly significant.

The latent class approach also generates additional information that is potentially very useful to recreational site managers, simply by identifying groups of users with particular demands. Planners and policy makers may be concerned with how changes to coastal sites will affect visitor numbers or the utility of the individuals that visit the sites. Being able to identify different segments of users within a count data modeling framework will allow such managers to better allocate resources between policy issues such as beach congestion, beach access, coastal access such as roads and trails, and beach developments and facilities. In our empirical investigation, for example, the results of the latent class corrected NB model suggest that policies impacting on water sport participation would have an impact on a larger group of beachgoers.

Given the relatively small sample size it would be wise to take a cautious view as to how representative the estimated welfare results are of the population of beach users in the west of Ireland. Nevertheless the estimated models still demonstrate how controlling for on-site sampling and unobserved het-

[11] Hynes, Hanley, and O'Donoghue (2009) highlight the fact that there are different types of boaters within a population of kayakers, using a random utility site choice latent class modeling framework, while Scarpa and Thiene (2005) do the same for rock-climbers. An early paper by Morey (1981) developed a model of skier behavior implicitly taking into account whether the skier was a novice, intermediate, or advanced in skill. The results of that study indicated that the number of days spent at a particular skiing site depended significantly on the individual's skiing ability.

erogeneity can have a significant impact on predicted trips taken and on welfare estimation. Also, it should be noted that Whitehead et al. (2008a) have shown that when the product of trips and consumer surplus per trip is taken as an estimate of consumer surplus per year in contingent behavior models, hypothetical bias may lead to upwardly biased seasonal consumer surplus estimates.[12] While this paper's contribution does not require the avoidance of this problem, we mention it in order to caution the reader who might wish to use the results for policy analysis.

[12] A possible solution to this problem is for the researcher to first ask respondents to report contingent behavior under the circumstances of no change in quality or site status prior to asking them to report contingent behavior under the circumstances of the change in the status quo.

It is important to state that while the focus of the paper was on a model of contingent behavior, the developed modeling framework is just as applicable to cases where data has been collected on-site in relation to trips taken by the same individuals over repeat time periods or on an individual's trip activity to alternative sites over a fixed period. Finally, an area for future research is to compare the welfare impacts derived using the latent class specification developed here to a count data model where the unobserved heterogeneity of the population with respect to the explanatory variables is specified as continuous rather than over finite segments (i.e., specifying the slopes as random coefficients). This would allow for a broader discussion of how unobserved heterogeneity could be best captured in on-site panel count data models.

APPENDIX

TABLE A1

Pooled and Panel Poisson and Negative Binomial Contingent Behavior Models Unadjusted for Truncation and Endogenous Stratification

	Poisson Pooled Count Data Model	Negative Binomial Pooled Count Data Model	Poisson Panel Count Data Model	Negative Binomial Panel Count Data Model
Age	0.001 (0.001)	0.001 (0.007)	0.105*** (0.023)	0.165*** (0.032)
Income	0.002*** (0.001)	0.002 (0.002)	− 0.001 (0.001)	0.001 (0.002)
Incidental visit to beach	− 0.724*** (0.075)	− 0.909*** (0 .189)	− 0.664*** (0.189)	− 0.780*** (0.243)
Member of recreation or environmental organization	0.471*** (0 .035)	0.389*** (0.116)	0.51*** (0.096)	0.333*** (0.092)
Contingent behavior	0.387*** (0.033)	0.429*** (0.099)	0.387*** (0.028)	0.418*** (0.049)
Travel cost	− 0.017*** (0 .002)	− 0.008 (0.005)	− 0.028*** (0.008)	− 0.029** (0.014)
Travel cost substitute site	0.001 (0 .001)	0.001 (0 .003)	0.017* (0.01)	0.01 (0.015)
Water sport participation	0.386*** (0 .038)	0.434** (0 .185)	0.613*** (0.069)	0.736*** (0.125)
Constant	2.373*** (0.044)	2.34*** (0.155)	1.607*** (0.127)	1.743*** (0.169)
Alpha		0.677*** (0.088)		0.022** (0.01)
Sigma			0.628*** (0.028)	0.805*** (0.053)
AIC	3,598	1,795	1,605	1,581
BIC	3,630	1,831	1,641	1,620
Hannan Quinn	3,611	1,809	1,620	1,597
Log likelihood	− 1,790	− 887	− 793	− 779

Note: Standard errors are in parentheses. The income variable has been rescaled by dividing by 1,000. AIC, Akaike information criterion; BIC, Bayesian information criterion.

* Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

Acknowledgments

This work is an output of the Socio-Economic Marine Research Unit (SEMRU) and was funded through the Beaufort Marine Research Award, which is carried out under the Sea Change Strategy and the Strategy for Science Technology and Innovation (2006–2013), with the support of the Marine Institute, funded under the Marine Research Sub-Programme of the National Development Plan 2007–2013.

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