Contingent Behavior Modeling for Dark Skies Valuation at Great Sand Dunes National Park *

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Abstract

Dark sky conservation is increasingly popular, requiring facility upgrades and community cooperation. This study assesses its economic benefits at Great Sand Dunes National Park and Preserve, a Gold Tier International Dark Sky Park. Through on-site surveys, we collected data on visitor behaviors, expenditures, and night sky perceptions. We introduced a continuum of contingent night sky brightness levels based on visitors' home locations and measured changes in visitation. Our Travel Cost-Contingent Behavior analysis shows each unit increase in nightlight decreases visitation by 0.05 days over five years. Using a weighted Latent Class Negative Binomial model, we estimate consumer welfare losses under escalating light pollution scenarios. If the park's night skies matched an average rural, suburban or urban area, visitors' consumer surplus would fall by about 3%, 23-24%, and 42-44%, respectively. These results underscore the substantial economic value of preserving dark skies.

JEL classification: Q26, Q51, Q56
Keywords: willingness-to-pay, dark sky conservation, nightlight pollution, travel cost model, contingent behavior model, national park, tourism

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1 Introduction

Preserving dark skies has emerged as a significant aspect of nature conservation, recognized for its ecological and health benefits such as maintaining biodiversity and protecting circadian rhythms (e.g., Argys, Averett, and Yang, 2021; Wang, Kaida, and Kaida, 2023; Boslett, Hill, Ma, and Zhang, 2021; Cao, Xu, and Yin, 2023; Seewagen and Adams, 2021; Karan, Saraswat, and Anusha, 2023). Concurrently, dark sky tourism is gaining popularity as people seek out pristine night skies for stargazing and astronomical experiences. In 2022, the Governor of Colorado signed the "Support Dark Sky Designation and Promotion in Colorado" Act, highlighting the state's commitment to dark sky preservation and its potential for tourism (Colorado General Assembly, 2022). The 2023 Conservation in the West Poll conducted by the State of the Rockies Project revealed that 69% of the respondents consider dark sky preservation a key conservation goal (State of the Rockies, 2023). Despite the increasing popularity of dark sky tourism, there is still a gap in research on its economic value. Understanding this economic value can inform the development of policies for dark sky preservation and offer a new perspective on nature conservation.

Great Sand Dunes National Park and Preserve (hereafter the "park") is located in southern Colorado and covers approximately 149,000 acres (National Park Service, 2024). The park draws over half a million visitors annually, contributing more than $30 million to the local economy in 2022 (Flyr and Koontz, 2023). Its high elevation, dry air, remote location, and low light and noise pollution create an ideal environment for stargazing (Underwood, 2015). In 2019, the park earned the Gold Tier International Dark Sky Park designation from DarkSky International. While this recognition attracts visitors, achieving and maintaining it involves significant costs, such as monitoring and updating lighting, creating dark sky education programs for the public, and working with nearby Alamosa and Saguache Counties to minimize light pollution (International Dark-Sky Association, 2024). Given the investment needed to preserve dark skies, gaining a better understanding of the benefits specifically derived from dark sky tourism is essential.

Our project quantifies the consumer surplus associated with dark sky conservation at the Great Sand Dunes. To support such estimation, we conducted on-site, in-person surveys with visitors at the park between October 20 and 22, 2023. Our survey collected comprehensive information on the visitors, including their points of origin, trip-taking behavior, expenditures during travel and in the local area, and perceptions of the night sky quality at the park. We asked whether they had spent time observing the night sky and requested them to compare its quality at the park to that at their residences. Importantly, we inquired how changes in the night sky at the park might affect their future visitation behavior.

To approximate the darkness of the night sky, we use cloudless nightlight data captured by the Visible Infrared Imaging Radiometer Suite (VIIRS) satellite, produced by the Earth Observation Group (Elvidge, Baugh, Zhizhin, and Hsu, 2013). The park had a baseline nightlight value of 0.28 in October 2023. For comparison, rural areas where our tourists originate had an average nightlight value of 1.82 in 2022, while urban areas averaged 32.08.

The primary finding of this project is that dark skies significantly enhance the tourism value of the park. Our main results are threefold. First, for each unit increase in nightlight at the site, a tourist's visitation decreases by 0.05 days over a five-year period. Second, while each day spent at the park yields substantial positive consumer welfare, we observe that the marginal consumer welfare diminishes rapidly as the number of visitation days increases. Third, we quantify the decrease in consumer welfare due to changes in night sky brightness, by combining our estimate of baseline consumer surplus with the estimated change in visitor behavior under a brighter night sky scenario. Specifically, our estimates indicate that if the night sky at the park were to become as bright as an average rural, suburban, or urban area, an average visitor would experience percent decreases in annual consumer surplus ranging from about 3% for rural brightness, 23–24% for suburban brightness, and 42–44% for urban brightness.[1]

[1] These percent decreases correspond to declines in annual consumer surplus for the average visitor of $4 to $18 for a transformation to average rural brightness, $39 to $159 for suburban brightness, and $72 to $291 for urban brightness.

Methodologically, our project contributes to the literature on public goods valuation. We design a survey that provides tangible and discrete contingent scenarios for a public good—night sky quality—that is continuous in scale. Nightlight pollution is continuous by nature, and the impression of whether a dark sky exists varies subjectively across individuals. To address this, we ask each respondent to compare the actual night sky at the park, a common baseline for all respondents, to the night sky at their homebase. This provides an individual-specific counterfactual state. Then, we examine whether their visitation days would change if the park's night sky became the same as at their home, while all other park attributes remained unchanged. This design creates a discrete and exact comparison for each respondent on an otherwise continuous matter. It also allows the comparison of the actual and contingent states to be accessible and understandable to each respondent.

In our analysis, we convert each respondent's homebase night sky—the contingent state—into a numerical value representing night sky darkness using VIIRS nightlight data. Pooling all responses creates a continuum of contingent states on nightlight pollution. This survey method extends studies in which the contingent scenario is binary or limited to a few discrete alternatives. We are not aware of previous studies that use a continuum of contingent states as opposed to a relatively small set of discrete contingent scenarios. Our approach preserves the benefit of contingent behavior methods by reducing potential survey response bias inherent in contingent valuation methods, while extending applicability to continuous and potentially non-measurable scenarios.

Furthermore, we employ a fixed-effect regression to remove unobserved biases that may correlate with both visitation behavior and nightlight levels at respondents' homebases. This unobserved bias is a unique endogeneity issue arising from our survey design, where contingent scenarios are respondent-dependent. Such an issue typically does not occur when studying contingent behaviors with only exogenous and discrete scenarios. By creating a panel of individuals across their historical and contingent states, we utilize individual fixed effects to control for person-specific unobserved biases. We do not find further significant demographic-based group-specific effects in robustness tests after controlling for individual fixed effects.

Finally, we address the challenges of truncation and endogenous stratification inherent in on-site data collection. On-site surveys typically capture responses only from visitors who have spent at least one day at the site, and frequent visitors are more likely to participate. Our survey design introduces a contingent scenario of night sky deterioration, allowing respondents to report zero visitation days under this counterfactual condition. By combining historical visitation data with contingent data, we create an individual-level panel that effectively mitigates the issue of truncation at zero.

However, endogenous stratification persists because frequent visitors are overrepresented in our sample. We apply the inverse visitation weight method proposed by Shi and Huang (2018), which adjusts for the higher likelihood of encountering frequent visitors in on-site surveys. Comparing unweighted and weighted regression models, we find that endogenous stratification biases the estimated impact of nightlight pollution towards zero. The weighted model reveals a stronger effect of nightlight pollution on visitation days.

Furthermore, we incorporate the Latent Class Negative Binomial (LCNB) regression model recommended by Hynes and Greene (2013) and Hynes and Greene (2016) to account for on-site sampling issues and respondent heterogeneity in the estimation of consumer welfare. We incorporate the Shi and Huang (2018) weight in addition to the LCNB, a combination of approaches not applied previously in this context to our knowledge. Without accounting for on-site sampling, our marginal consumer welfare leans toward zero, while LCNB regression with inverse visitation weight estimates a much higher marginal consumer welfare. This is because visitors have a sizable positive yet diminishing marginal utility from visiting the park. Frequent visitors are at the higher and flatter end of the utility function, with a relatively low marginal value for each day at the park, while infrequent visitors derive a much higher marginal value. Correcting for on-site sampling endogenous stratification results in weighing the average marginal value towards that of infrequent visitors.

The rest of the paper proceeds as follows. Section 2 overviews literature on night sky tourism, contingent behavior methods, and on-site sampling. Section 3 describes the survey methodology, empirical methods, and our collected data. Section 4 presents estimation results. Section 5 concludes the paper.

2 Literature

The body of literature examining the implications of nightlight pollution has predominantly focused on human health and biodiversity (e.g., Argys et al., 2021; Wang et al., 2023; Boslett et al., 2021; Cao et al., 2023; Seewagen and Adams, 2021; Karan et al., 2023). Research specifically addressing the economics of dark sky tourism is considerably limited. Some studies have provided preliminary insights. Collison and Poe (2013) conducted research in Bryce Canyon National Park and found that up to 10% of park visitors engaged in either formal dark sky programs or informal dark sky-related activities. Additionally, Mitchell and Gallaway (2019) projected that tourists prioritizing dark skies would contribute $5.8 billion to the Colorado Plateau region over a decade, generating higher wages and creating over 10,000 jobs annually. Rodrigues and Peroff (2014) highlighted the role of dark sky areas as distinctive tourism destinations, potentially attracting visitors over comparable sites without dark sky designations. Hvenegaard and Banack (2024) surveyed 31 visitors at the Jasper Dark Sky Festival in Alberta, Canada to investigate visitor outcomes such as attitudes, satisfaction, learning, and behavior changes. They found that, while visitors reported high levels of satisfaction, learning, and the importance of protecting dark skies, only 42% intended to change any of their behaviors to help protect dark skies. Simpson and Hanna (2010) used contingent valuation to estimate willingness to pay for improved night skies but faced limitations due to small and specific student samples and hypothetical inflation.

The ecotourism literature emphasizes the importance of perceived environmental value in influencing tourist behavior (e.g., Carvache-Franco, Carrascosa-López, and Carvache-Franco, 2021; Donici and Dumitras, 2024). Carvache-Franco et al. (2021) find that functional and emotional values are significant predictors of tourist satisfaction and intentions to recommend destinations. Although not focused on dark sky tourism specifically, these findings underscore the broader significance of environmental quality in nature-based tourism. Additionally, studies suggest that the benefits associated with ecotourism can increase local support for conservation efforts (Lindberg, Enriquez, and Sproule, 1996).

To our knowledge, only one other study—Heberling and Templeton (2009)—has conducted a rigorous statistical analysis to estimate the consumer welfare of trips to our study site. They employed a travel cost model (TCM) using only revealed preference data, utilizing secondary data collected by the National Park Service to enhance understanding of visitor patterns. Their contribution augmented the limited literature on the valuation of national parks in the U.S. and demonstrated the potential for using secondary survey data not specifically designed to support a TCM. In contrast, our survey is specifically designed to support both a TCM as well as a model combining TCM and the contingent behavior method (CBM). By incorporating both stated and revealed preference data, our research extends previous studies focused on recreation on federal lands.

There exists a broad range of previous studies in the literature that have used the CBM to estimate the effects of potential changes in various environmental attributes (e.g., Loomis, 1993; Cameron, Shaw, Ragland, Callaway, and Keefe, 1996; Eiswerth, Englin, Fadali, and Shaw, 2000; Loomis, 2002; Mathews, Homans, and Easter, 2002; Bhat, 2003; Hesseln, Loomis, and González-Cabán, 2004; Egan and Herriges, 2006; Eiswerth, Kashian, and Skidmore, 2008; Hynes and Greene, 2013, 2016; Voltaire and Koutchade, 2020; Börger, Mmonwa, and Campbell, 2024). One of the advantages of CBM lies in its combining of revealed and stated preference methods, an approach suggested and used by Cameron (1992), Adamowicz, Louviere, and Williams (1994), and Kling (1997) and assessed by Whitehead, Pattanayak, Van Houtven, and Gelso (2008). CBM may be less prone to response bias than the contingent valuation method (CVM), in which respondents may have an incentive to either understate or overstate their true willingness to pay for an improvement (or deterioration) in an environmental attribute (e.g. Meyer and Yang, 2016).

A CBM is an extension of the TCM, with revealed preference data supplemented by stated preference observations for the same set of recreators. In CBM, as in TCM, count data models are generally preferred. Their application to consumers is grounded in micro theory (Hellerstein and Mendelsohn, 1993) and their employment in recreation demand modeling is pervasive, with early examples in the literature including but not limited to Shaw (1988), Creel and Loomis (1990), Englin and Shonkwiler (1995), Shonkwiler and Shaw (1996), and Englin, Boxall, and Watson (1998). Count data models are suitable if a dependent variable of interest assumes nonnegative integer values and the measures to be estimated involve baseline levels and changes in measures such as aggregate recreation days and consumer surplus.

Contingent scenarios designed for CBM may be based on either objective or subjective indications of an environmental attribute. While contingent scenarios in the literature are often based partly or entirely on objective and numerical metrics, researchers have pointed out that numerical measures of environmental attributes may be difficult for many people to comprehend. Furthermore, it may be challenging to compare two different quantitative measures of an attribute and assess what the differences might mean for recreation, aesthetic benefits, and overall satisfaction. For example, researchers have noted the difficulty that consumers have in assessing the differences among and implications of alternative pollutant loading levels or ambient pollution concentrations (e.g., Smith and Desvousges, 1985; Whitehead, Haab, and Huang, 2000). Our CBM design relies on subjective references to the condition of the night sky at the location where each respondent resides.

In both CBM and the broader context of TCM, the issues of truncation and endogenous stratification resulting from on-site sampling are well-known. The literature has addressed these concerns through various methods. Initial approaches involved corrections for count data models using Poisson (Shaw, 1988) and negative binomial (Englin and Shonkwiler, 1995) distributions. Subsequent studies have employed panel data techniques to account for on-site sampling effects (e.g., Egan and Herriges, 2006; Beaumais and Appéré, 2010; Moeltner and Shonkwiler, 2010). Additionally, Latent Class (LC) models have been utilized in CBM to correct for on-site sampling and to account for correlations between revealed (actual) and contingent trip data (e.g., Hynes and Greene, 2013, 2016). Shi and Huang (2018) introduced a negative visitation weight to adjust the on-site sample, aiming to better reflect the underlying population of recreational visitors.

At the same time, empirical evidence on comparing TCM models correcting and not correcting for stratification has been mixed. For example, Ovaskainen, Mikkola, and Pouta (2001) concluded that a model not adjusted for stratification could be acceptable for estimating the aggregate benefits of a recreation site. In contrast, other studies have found significant differences between corrected and uncorrected models in per-person baseline consumer surplus and changes in consumer surplus due to attribute changes (e.g., Hynes and Greene, 2013). Some research indicates that while correcting for on-site sampling significantly affects trip demand estimation, it has a relatively small impact on estimated per-person consumer surplus (e.g., Egan and Herriges, 2006; Shi and Huang, 2018). With respect specifically to CBM models, Hynes and Greene (2013) and Voltaire and Koutchade (2020) have noted that the failure to fully correct such models for endogenous stratification and correlation between revealed and contingent observations is quite common, specifically regarding CBM scenarios involving a deterioration in environmental quality. In our models, we address potential on-site sampling issues.

Shi and Huang (2018) employ a TCM using only actual trips rather than a CBM with combined actual and contingent trips. They observe the limitations in standard corrections for on-site sampling in the literature. Specifically, the effectiveness of such adjustments heavily depends on the accuracy of the population distribution assumptions. If the true population distribution is incorrectly specified, the corrections embedded in the assumed probability density function can be fallacious. Instead, Shi and Huang (2018) propose an alternative method to account for on-site sampling bias: they use the sample distribution of the collected data to reweigh the observations. Instead of scaling up the assumed population distribution to match the on-site sample, they empirically down-scale the observed on-site sample to estimate the unknown population distribution more accurately. They conclude that this reweighting approach performs better than the standard corrections when the underlying population distribution differs from the assumed distribution, and performs comparably well even in the absence of such differences. This technique is illustrated elsewhere in the literature (e.g., Wooldridge, 2002). Our methods adopt the inverse reweighting approach to account for potential on-site sampling bias.

Other important issues in CBM applications include accounting for unobserved respondent heterogeneity and possible correlation between the revealed trips and contingent trips data collected from any given respondent in a CBM survey. Hynes and Greene (2013) point out that the simple pooling of revealed and contingent trip observations, though quite common, does not address the likelihood of correlation between the revealed and contingent data. They develop an innovative panel data model with a latent class structure to account for these factors along with potential on-site sampling issues. We adopt a fixed effect model to account for individual heterogeneity in estimating contingent behaviors. However, fixed effect regression absorbs the individual constant travel cost, which is crucial in a TCM to estimate consumer welfare. In our estimation of consumer welfare, we adopt a latent class estimation following Hynes and Greene (2013).

3 Methods and Data

3.1 Contingent behavior scenario and survey design

We design a survey and research methodology that utilizes and integrates techniques from both the TCM and CBM methods.[2] Our survey design supports the TCM framework by collecting data on the number of trips and days per trip that visitors take and the round-trip cost of traveling to the recreation site. To implement the CBM, we present respondents with a hypothetical scenario in which the night sky at the park differs from its current condition. We then inquire about how this change might influence their visitation behavior. The CBM provides the benefit of reduced response bias compared to the CVM. Furthermore, it enables us to examine how consumers might react to environmental conditions that are outside their prior experiences at the site.

In designing our contingent behavior scenario, we aim to describe a simple and familiar alternative night sky at the park to which each respondent can directly relate. The specific scenario offered to each respondent is shown in Figure 1.

6a. Specifically, if the night sky at *the Great Sand Dunes* looked identical to the sky at your home base *(where you live for most of the year)*, that is, you could see about the same amount of stars here as at your home base, do you think you would change your visiting plans *(that is, either the number of visits or the length of those visits)* to *the Great Sand Dunes* over the next 5 years? *Assume that, even if we had more or fewer stars to see at night at the Great Sand Dunes, the nature of the other amenities and qualities of the Great Sand Dunes would stay the same.*

Figure 1: Contingent behavior scenario offered to respondents.

If a respondent replies "Yes" to the initial question regarding the contingent behavior scenario, they are asked to provide details about how they think they would change their behavior over the next five years. Specifically, we ask how many fewer trips they would take and the degree to which trips in the future might be of a different duration.

One of the major innovations in our research design is how we measure and present the

[2]The full survey is included in Appendix A.

quality of the park's dark sky (and potential changes to it) to respondents. Dark sky quality is inherently subjective, and its deterioration through nightlight pollution is continuous. Scientific measurements of night sky darkness are not intuitive for the average visitor. To make the concept accessible, we asked respondents to compare the night sky at the park to the night sky they experience at home. This creates a discrete and familiar scenario for each person. Then, by pooling all responses and their associated scenarios, we create a synthetic continuous set of contingent nightlight pollution scenarios for our study. This method allows us to analyze a wide range of potential night sky conditions as a continuous variable.

In addition to actual past and contingent future trip-taking behavior, our survey asks a number of other questions to support our analyses. This includes a question about the location of the visitor's homebase (residence) and questions about expenses both during travel to and from the site and during visitors' time spent in the area. Our survey also includes questions about demographics (e.g., age, education, occupation, and income), whether the visitor had spent time looking at the night sky at the park, and the visitor's impressions of the quality of the night sky and stars there. These questions allow us to characterize visitors' attitudes, backgrounds, expenses, and tourism behavior.

3.2 Survey implementation

We collected our data employing a hardcopy visitor intercept survey. Visitors were intercepted at two locations within the park: 1) the approach paths from the Visitor Center parking lot to the Visitor Center, and 2) the primary and the largest parking lot that feeds the main access points to the dunes. The survey was implemented over three days: October 20–22, 2023. Visitors were intercepted, provided a brief background on the survey, and assisted with survey completion as necessary.

We used an intercept format (rather than, for example, a mail survey format) due to financial constraints. In addition, the characteristics of our site and our research objectives recommend an intercept survey. First, visitors to the park typically originate from most states in the U.S. as well as many other nations (Le and Littlejohn, 2003). However, as a percentage of the overall population, very few recreators have ever visited the park, with annual visits in recent years at about a half million (Flyr and Koontz, 2023). Therefore, for the study of recreation and perceptions of night sky quality at the park, implementing a mail survey was not feasible with the budget available.

Second, our primary aim was to contact individuals who visit the park in its present, recently bestowed capacity as a Gold Tier International Dark Sky Park. We then assess how visitors might change their trip-taking behavior in the future if the night sky at the park were to become less dark. Therefore, in addition to the fiscal constraints present for our study's implementation, our methods and objectives suggest intercept contact with current visitors rather than a sample of participants and nonparticipants via a mail or telephone survey.

Third, since our contingent scenario involves a diminishment rather than an improvement in an environmental attribute, the issue of new recreation potentially engendered by enhanced quality is not present. Thus, the study differs from many previous CBM studies, and it is not necessary to survey nonparticipants.

Five survey takers worked as a team to intercept visitors and guide them through the survey. The number of completed surveys collected was similar across the five survey takers. Subsequent empirical tests do not find appreciable differences in visitor responses as a function of the survey worker's identity.

3.3 Empirical methods

As described in the literature review section, our method uses a count data model similar to approaches employed in numerous previous studies of the value of outdoor recreation. The Poisson and negative binomial are commonly used. We favor the application of the negative binomial *a priori* as it does not assume equidispersion. Subsequent analysis also confirms overdispersion in this particular data set. The general form of the model follows that of

Hynes and Greene (2013) and Hynes and Greene (2016), and is described by Equation (1):

$$P(\text{days}_{it} \mid \text{days}_{it} > 0, s_i, c_i, nl_{it}) = F(\text{days}_{it} \mid s_i, c_i, nl_{it}; \gamma) \tag{1}$$

where days_{it} is the number of visit days that visitor i takes in the last five years (t = actual) or in the next five years (t = counterfactual); s_i is a vector of individual demographic characteristics; c_i is the round-trip travel cost to the site; nl_{it} is the nightlight feature of the site; and γ is a vector of unknown parameters. While all other variables are collected through the survey, we use the cloudless nightlights reported by VIIRS to approximate the darkness of each area.

The individual demographic factors are important control variables for the negative binomial regression because of potential unobserved individual differences. However, travel cost and counterfactual nightlight tend to strongly correlate with most of the demographic variables we surveyed. For instance, individuals living in urban centers are often correlated with brighter nightlights. There are often systematic correlations between homebase nightlight and income and education levels. To avoid multicollinearity with our main variables nl_{it} and c_i, we only include age_i and age_i^2. The inclusion of age_i^2 in trip demand models is common in order to accommodate potential nonlinearity in the influence of age. To facilitate hypothesis testing even under model misspecification, we use White's standard errors (White, 1982).

Our survey design establishes a continuum of counterfactual states that are dependent on the homebase of each respondent. However, this also introduces unobserved biases if we regress the counterfactual nightlights on the associated contingent visitation behavior. For example, respondents may have individual-specific preferences that lead to different visitation behaviors, independent of the night sky conditions. Moreover, group-specific biases may exist. For example, respondents living in urban centers with brighter nightlights, a higher value in the counterfactual scenario, may also have group-specific preferences that lead to visitation behavior to dark sky preserves that are systematically different from those visiting from rural areas.

We exploit an individual fixed effect model to tease out individual-specific factors biasing our estimation of the impact of nightlight pollution on contingent visitation behaviors. Specifically, we stack the actual historical visitation behavior associated with the actual nightlight at the site on top of the contingent scenarios and their contingent visitations for each respondent. This creates a panel for each respondent of actual and contingent data. The individual fixed effect regression controls for all factors idiosyncratic to each visitor and returns an estimate of visitation behavior contingent on a marginal change in nightlight at the site that is common to all visitors. Equation 2 describes the fixed effect negative binomial regression (FENB). Since the individual fixed effect for visitor i includes all constant individual factors, s_i and c_i drop out.

$$P(\text{days}_{it} \mid \text{days}_{it} > 0, nl_{it}, \alpha_i) = F(\text{days}_{it} \mid nl_{it}, \alpha_i; \gamma) \tag{2}$$

Further, we modify Equation 2 by adding a term that interacts nl_{it} with the respondent's existing demographics to infer whether any group-specific (g) factors further moderate our estimation:

$$P(\text{days}_{it} \mid \text{days}_{it} > 0, nl_{it}, \text{group}_g, \alpha_i) = F\Big(\text{days}_{it} \mid nl_{it}, nl_{it} \times 1(\text{group}_g), \alpha_i; \gamma\Big) \tag{3}$$

Equation 3 describes our regression controlling for group-specific effects. We group individuals based on their responses regarding their homebase type (rural, suburban, urban), whether they are from Colorado or out of state, age, education, and whether they have seen the night sky at the park. If the coefficients on the interaction terms are statistically significantly different from zero, we can infer that some group-specific variation impacts their contingent behavior in addition to individual-specific factors.

Our research aims to estimate the consumer welfare value associated with a marginal change in nightlight pollution. Though the FENB works well in correcting individual heterogeneity, it drops the individual-specific travel cost variable, which is key for deriving marginal valuation in consumer welfare. Therefore, in addition, we follow Hynes and Greene (2013) and Hynes and Greene (2016) in creating a latent class negative binomial regression (LCNB) that incorporates both nightlight and travel cost information from Equation 1. We adjust their model using our general form in Equation (4):

$$P(\text{days}_{it} \mid \text{days}_{it} > 0, s_i, c_i, nl_{it}, \text{class} = \theta) = F(\text{days}_{it} \mid s_i, c_i, nl_{it}; \gamma_\theta) \tag{4}$$

To account for endogenous stratification, we follow Shi and Huang (2018) and weigh each observation i by $1/\text{days}_{it}$ (t = actual) to correct for the overrepresentation of more frequent trip-takers sampled via the on-site survey. We apply this correction to both Equations 2 and 4. This yields a weighted fixed effect negative binomial regression (weighted FENB) and a weighted latent class negative binomial regression (weighted LCNB).

Our estimates of contingent behavior under increased nightlight from the weighted LCNB and the weighted FENB models are largely consistent. This allows us to infer that the weighted LCNB regression effectively accounts for endogenous stratification and respondent heterogeneity.

We use the weighted LCNB to infer the consumer welfare value for a marginal change in nightlight at the park. In a negative binomial count model, consumer surplus per day is calculated as: CS per day $= -\frac{1}{\gamma_c}$, where γ_c is the estimated coefficient for the travel cost variable (Haab and McConnell, 2002). Note that days_{it} represents visit days per person (party-days $\times$ party size). This specification has the advantage of adding information as well as variation to the travel demand dependent variable (e.g., Bowker, English, and Donovan, 1996; Bhat, 2003; Martinez-Espineira and Amoako-Tuffour, 2008; Heberling and Templeton, 2009).

After estimating the total consumer welfare for each day of visit at the site, we can combine it with the coefficient of nl_{it}, which represents the marginal visitation change due to nightlight pollution, to estimate the welfare value of a marginal change to nightlight at the site.

3.4 Data description

The project team collected 367 completed surveys, each corresponding to a visitor party comprising one or more individuals. From these responses, we remove those that do not provide an identifiable home location or days of presence at the park. We further exclude international travelers and travelers with a home location in Alaska and Hawaii from the present analysis. This leaves us with 330 visitor parties. Table 1 provides descriptive statistics of the responses that we use for the remaining analysis.

According to our survey data, visitors took an average of 1.91 trips to the park in the last five years, spending 1.58 days at the park per trip. This results in an average of 2.68 visitation days per person over the last five-year period.

Next, we ask tourists if they would take fewer trips and/or stay for fewer days per trip in the next five years if the night sky at the park were to look the same as it does at their home while all amenities and other qualities of the park stayed the same. In response, 47% of the respondents indicate that they would spend fewer days at or take fewer trips to the park in the next five years. The average visitation days per person over the next five years dropped to 1.60 days in this hypothetical scenario.

We estimate each respondent's travel cost to and from the park by combining the national park private vehicle access fee of $25 and an estimated round-trip fuel cost between the site and the respondent's homebase. We first estimate the driving distance using the crow-fly distance between the reported homebase and adjusting it with a coefficient of 1.417, following Boscoe, Henry, and Zdeb (2012). We then apply the 2010 US fleetwide mileage per gallon of 17.4 mpg and the average gas price per gallon of $3.613 for regular grade all formulations retail gas in October 2023 (U.S. Energy Information Administration, 2024a,b). As a comparison, the fleetwide mileage per gallon in 2022 is 18.5 mpg. We use the 2010 mpg

Table 1: Descriptive statistics.

Category	Mean	St.D.	Observations
Number of past days	2.68	3.14	330
Number of contingent days	1.60	2.74	329
Transportation cost per day	300.89	303.30	330
Homebase light	17.39	18.74	329
Age			
16–24	11.52	31.97	38
25–34	26.36	44.13	87
35–44	22.73	41.97	75
45–54	13.33	34.05	44
55–64	11.21	31.60	37
65+	14.85	35.61	49
Education			
High school or less	8.39	27.76	27
Some college/Associate degree	8.07	27.29	26
College degree	44.72	49.80	144
Graduate degree	38.82	48.81	125
Occupation			
Primary and Industrial Services	5.96	23.72	14
Trade, Transportation, Retail, and Admin Services	8.94	28.59	21
Finance, Real Estate, Information, and Professional Services	51.91	50.07	122
Educational, Health, and Social Services	21.70	41.31	51
Arts, Entertainment, Recreation, Public and Other Services	11.49	31.96	235
Homebase			
Urban	26.97	44.45	89
Suburban	53.33	49.96	176
Rural	19.70	39.83	65
Homebase is in Colorado			
Yes	43.03	49.59	142
No	56.97	49.59	188
First time visiting Great Sand Dunes			
Yes	54.85	49.84	181
No	45.15	49.84	149
Have seen night sky at Great Sand Dunes			
Yes	42.81	49.56	140
No	57.19	49.56	187

Note: This table presents descriptive statistics. Homebase light is based on the 2022 average monthly cloudless nightlight levels from VIIRS for each respondent's homebase. Other variables are derived from survey responses. Except for the first panel, all categorical variables are expressed as percentages of responses.

value because the average age of light motor vehicles in the US is 12.5 years (Bureau of Transportation Statistics, 2024). Lastly, we divide the estimated total travel cost for each visitor party by the number of days each visitor party spent at the site; it gives an average estimated transportation cost per day of $300.89.

Researchers have taken varied approaches to measuring the opportunity cost of time for recreational travel, with no consensus (e.g., Feather and Shaw, 1999; Parsons, 2017; Czajkowski, Giergiczny, Kronenberg, and Englin, 2019). Parsons (2017) notes that about half of studies use one-third of the hourly wage, while others use different values, and some suggest travel itself provides positive utility. Czajkowski et al. (2019) observed that the cost of travel time remains a persistent uncertainty, and that assumptions linking travel time to a fixed share of wages are unreliable, as many respondents report no desire for shorter travel. Given these complexities, we exclude travel time costs from round-trip travel costs.

Nightlight is measured as the average monthly cloudless nightlights captured by VIIRS (Elvidge et al., 2013), except for the park area, where the October 2023 value is used to reflect the actual night sky during data collection. For each respondent's counterfactual scenario, we use the 2022 average monthly cloudless nightlight levels for their homebase zip code to provide a general impression of the homebase night sky. We opt not to measure it over a particularly short timeframe, as people may recall the homebase night sky based on a long-term impression rather than anomalies that could affect a specific month. As a reference, the Great Sand Dunes had a nightlight value of 0.28 in October 2023, compared to an average monthly homebase value of 17.39 in 2022.

We further collect demographic information from each respondent. Approximately 49% of visitors are aged between 25 and 44. Over 83% of visitors hold at least a college degree. Excluding retirees, students, and full-time homemakers, most visitors are employed in professional fields (Finance, Real Estate, Information, and Professional Services) and public services (Educational, Health, and Social Services). More than 50% of visitors come from suburban areas, while 27% are from urban locations. Forty-three percent of respondents are traveling from within Colorado. About 55% of respondents reported that it was their first time at the park, and 57% have yet to see the night sky in the park area. We do not exclude respondents who have not seen the night sky in our survey, as this allows us to maintain a larger sample base and not overlook visitors who may wish to stargaze during their current or future visits to the park. Our surveyors informed visitors about the site's International Dark Sky Park designation and described its dark sky scenery to visitors as they completed the survey. We conduct a robustness check in the following section to show that respondents who have yet to see the night sky do not overstate the contingent value of the night sky.

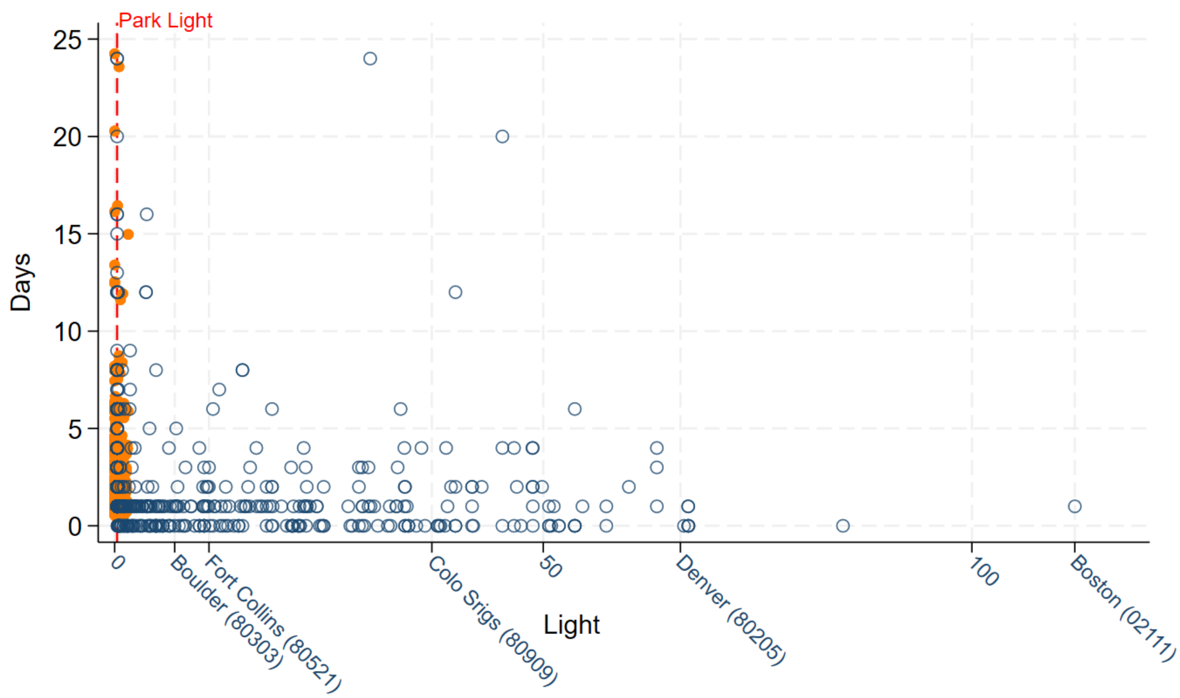

Figure 2: Counterfactual nightlight levels at the park and reported visitation days.

Note: This figure compares respondents' reported visitation days over the next five years under different nightlight conditions. The red line marks the park's current nightlight level (0.28). The horizontal axis is the counterfactual nightlight level, and the vertical axis is the reported visitation days.

In Figure 2, we compare the reported total visitation days per person over the next five years if the night sky were to become brighter. The red line near the origin indicates the current level of light at the park, which is a value of 0.28. If the sky were to resemble that of Fort Collins (80521), tourists state that they would spend 0.81 fewer days on average at the park in the next five years. If it were to resemble that of Denver (80205), tourists state that they would spend 1.51 fewer days on average at the park in the next five years.

4 Results

4.1 Nightlight pollution impacts on visitation behavior

We first analyze whether an increase in nightlight pollution impacts tourist visitation days to the site and present the results in Table 2. Column (1) displays the regression results using an NB model without adjusting for endogenous stratification or individual fixed effects. Columns (2) and (3) show the results using Fixed Effect regression with NB distribution (FENB). We employ the Shi and Huang (2018) method to adjust for endogenous stratification by applying the inverse of visit days as a weight for the weighted FENB regression in Column (3). The estimated coefficient for nightlight pollution (*nl*) from the NB regression in Column (1) is negative, as expected, and statistically significant at the 5% level. As discussed in previous sections, the NB model (Column (1)) does not account for on-site survey endogenous stratification or individual heterogeneity. Once we address these factors, the estimated coefficient for nightlight increases in absolute value and becomes statistically significant at the 1% level.

We consider the weighted FENB regression in Column (3) to be our benchmark estimation of tourists' contingent behavior regarding nightlight pollution. In addition to our preference for it *a priori* due to its corrections for endogenous stratification and individual heterogeneity, it also has the lowest absolute log-likelihood value and the lowest Akaike information criterion (AIC) score, indicating the best fit for our data. Each unit increase in nightlight pollution at the site decreases a visitor's visitation by approximately 1.88% (calculated using 1-exp(0.0186)). Considering that the average per-person visitation days over the past five years is 2.68, a 1.88% reduction translates to about 0.05 days lost per person in the next five years for each unit of deterioration in nightlight pollution.

Table 2: Regression results: impact of nightlight pollution on visitation days.

	(1) NB	(2) FENB	(3) weighted FENB
nightlight	-0.0145**	-0.0166***	-0.0186***
	(0.0053)	(0.0027)	(0.0039)
travel cost	-0.0019***		
	(0.0002)		
age	-0.0585		
	(0.0311)		
age^2	0.0007*		
	(0.0003)		
constant	2.6288***	3.2444***	17.3171
	(0.7493)	(0.5601)	(841.9662)
lnalpha	-0.0571		
	(0.1606)		
AIC	2675.567	772.0926	365.8567
Log likelihood	-1331.7835	-384.0463	-180.92834
Observations	657	662	662

Note: Standard errors in parentheses. AIC, Akaike information criterion. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

4.2 Robustness check on group-specific factors

As discussed, group-specific factors can bias our estimation of visitation behavior change due to nightlight pollution. Table 3 provides a series of robustness checks based on respondent demographics. Each column is a FENB regression based on Column (2) of Table 2, augmented with interaction terms of each group and nightlight.[3] Across Columns (1)-(5), we do not find statistical significance in the interaction terms; hence, we cannot reject the null hypothesis and infer that group-specific factors do not affect the impact of nightlight pollution on visitation behavior. Importantly, the coefficients on nightlight demonstrate consistent statistical significance. Though varying from -0.0155 to -0.0231, they fall within the 95% confidence interval of benchmark estimation in Column (3) of Table 2 without any group interaction terms.[4]

[3]Ideally, we would conduct the weighted FENB as in Column (3) of Table 2. Given the limited sample size, the added interaction terms prevent the weighted regression from reaching convergence.

[4]Table 2 Column 3, the 95% confidence interval for light is [-0.0262,-0.0110].

Table 3: Robustness check on group-specific effects.

	(1) Homebase	(2) Age	(3) Education	(4) Colorado	(5) Have seen
nightlight	-0.0155***	-0.0167***	-0.0226**	-0.0227***	-0.0231***
	(0.0032)	(0.0033)	(0.0093)	(0.0064)	(0.0059)
nightlight×suburban	-0.0036				
	(0.0055)				
nightlight×rural	0.0016				
	(0.0401)				
nightlight×age2		-0.0060			
		(0.0070)			
nightlight×age3		0.0055			
		(0.0059)			
nightlight×somecollege			0.0034		
			(0.0156)		
nightlight×college			0.0099		
			(0.0100)		
nightlight×grad			0.0041		
			(0.0100)		
nightlight×colorado				0.0074	
				(0.0070)	
nightlight×seen					0.0084
					(0.0066)
constant	3.2096***	3.3732***	3.3111***	3.3331***	3.3866***
	(0.5523)	(0.6657)	(0.5771)	(0.6101)	(0.6428)
Observations	662	662	646	662	656
Individual FE	Yes	Yes	Yes	Yes	Yes

Note: This table reports FENB regressions with group-specific interaction terms. Column (1) groups individuals by homebase (rural, suburban, urban - omitted). Column (2) groups by age (age1 - omitted: <36; age2: 36-55; age3: over 55). Column (3) groups by education (high school or below - omitted, some college, college, graduate). Column (4) groups by residency (Colorado vs. out-of-state - omitted). Column (5) groups by whether individuals have seen the park's night sky. Standard errors in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

Specifically, Columns (1)-(4) of Table 3 describe the visitor's inherent demographics. Column (5) focuses on whether the visitor has seen the night sky. While surveying the visitors, our surveyors described the Gold Tier status of the night sky at the park to visitors before posing the contingent scenario questions. Our goal is to establish a baseline understanding of the dark sky at the site common across all visitors without losing first-time visitors who have yet to observe the night sky. Column (5) is a robustness check that our description does not inflate the visitor's stated contingent behavior change.

4.3 Baseline consumer surplus of visits to the park

The advantage of the NB travel cost model in Column (1) of Table 2 is that it establishes a consumer welfare estimation for each day at the site. However, given endogenous stratification due to on-site sampling and individual heterogeneity, we augment it with a set of Latent Class NB (LCNB) models, following Hynes and Greene (2016). Moreover, we compare a two-latent-class NB model with one augmented with inverse visit-day weight, following Shi and Huang (2018). Hynes and Greene (2016) argue that the LCNB effectively accounts for on-site sampling issues and response heterogeneity. In this section, we show that weighing LCNB with Shi and Huang (2018) weight better accounts for the heterogeneity and on-site sampling given our unique survey design.

Column (1) of Table 4 shows that a two-class LCNB without weighting trenches the sample with a 94% probability for Class 1 and a 6% probability for Class 2. Class 1 has an average number of visit days of 1.76, while Class 2 has 38.82. After weighing the sample with inverse visit days, Column (2) reports a Class 1 probability of 5% and Class 2 of 95%. Weighted LCNB has an average number of visit days of 3.73 for Class 1 and 1.0 for Class 2. This suggests that the Shi and Huang (2018) weight method discounts high visitation observations and allows the latent class methods to split the sample based on further heterogeneities in respondents. Overall, the weighted Latent 2 Class NB in Column (2) of Table 4 best fits our on-site sampling data, given its lower absolute value in log-likelihood and AIC score. Therefore, we consider the weighted LCNB as our benchmark to estimate the consumer surplus value.

We inverse the coefficient for travel cost and adjust it by the average party size of 2.591 to calculate the average consumer surplus. Both latent classes of Columns (1) and (2) have statistically significant coefficients on travel cost. Column (1) suggests a consumer surplus of \$350.83 from Class 1 and \$64.45 from Class 2 per day per person at the site. After weighing the sample towards lower visitation days, Column (2) suggests consumer welfare of \$107.29 from Class 1 and \$1286.38 from Class 2. Following Hynes and Greene (2016), the unweighted LCNB provides an average consumer surplus of \$323.95 per visitor per day using the respective class probabilities. The weighted LCNB provides an average of \$1226.29 per visitor per day.[5]

The coefficient for *nl* reflects the estimation of the consumer's change in visitation behavior due to nightlight pollution. The unweighted LCNB has an estimated coefficient of -0.018 for Class 1 (significant at the 1% level), while the coefficient is statistically insignificant for Class 2. The weighted LCNB shows -0.0193 for Class 2 (significant at the 1% level), whereas it is statistically insignificant for Class 1. Both coefficients fall within the 95% confidence interval of the estimation in Column (3) of Table 2. Since the estimated coefficient is statistically insignificant for one of the classes in each model, we do not include it in calculating the overall contingent behavior. Following Hynes and Greene (2016), the overall marginal change in visitation for a one-unit increase in nightlight is -0.0169 for the unweighted LCNB and -0.0183 for the weighted LCNB.

In the next section, we link the estimated change in visitation due to nightlight pollution with the calculated daily total consumer surplus at the site to assess the consumer's welfare

[5] We conducted further heterogeneity analysis, decomposing the sample into small visitation day windows, particularly, for days 0-5, 1-5, 2-5, 6-12, 6-16, and 6-20. Given the small sample size, we can only use unweighted NB and weighted NB regressions. Our estimates suggest a diminishing marginal utility for days spent at the park. Visitors who spend fewer days at the park derive the highest marginal utility for each additional day. In comparison, visitors who spend more days derive the lowest marginal utility for each additional day. Weighing the sample towards low visitation days using the Shi and Huang (2018) weighting method adjusts the estimated consumer welfare towards the origin of the utility curve, hence the high marginal value.

Table 4: Regression results for latent two-class NB and weighted latent two-class NB models.

	LCNB		Weighted LCNB	
	(1)	(2)	(3)	(4)
	Class 1	Class 2	Class 1	Class 2
nightlight	-0.0180***	-0.0014	-0.0075	-0.0193***
	(0.0030)	(0.0085)	(0.0043)	(0.0047)
travel cost	-0.0011***	-0.0060***	-0.0036***	-0.0003**
	(0.0002)	(0.0013)	(0.0005)	(0.0001)
age	0.0090	-0.3819***	-0.0143	0.0063
	(0.0164)	(0.0597)	(0.0191)	(0.0107)
age^2	-0.0002	0.0035***	0.0003	-0.0001
	(0.0002)	(0.0006)	(0.0002)	(0.0001)
constant	0.9448**	2.1948***	12.6836***	0.1341
	(0.3413)	(0.3727)	(1.5465)	(0.2397)
lnalpha in latent class	-1.3471***	-1.3471***	-4.6695***	-4.6695***
	(0.1956)	(0.1956)	(1.1451)	(1.1451)
latent class probability	0.9376	0.0624	0.05096	0.94904
	(0.01587)	(0.01587)	(0.00975)	(0.00975)
latent class average days	1.764	38.8185	3.729	1.00185
	(0.08170)	(16.7264)	(0.28705)	(0.03020)
AIC	2485.878		1176.331	
Log likelihood	-1230.9388		-576.1653	
Observations	657		657	

Note: This table compares the results of a two-class LCNB regression with those of a weighted two-class LCNB regression using Shi and Huang (2018) weight. AIC, Akaike information criterion. Standard errors in parentheses. * Significance at the 10% level; ** significance at the 5% level; *** significance at the 1% level.

valuation of nightlight pollution in monetary terms.

4.4 Welfare valuation of nightlight pollution

An important feature of our approach is that the contingent scenario is a continuous space; therefore, each visitor has a different comparison point. Our regression analysis controls for individual factors and shows the mean behavior change in visitation days due to a marginal increase in nightlight pollution.

To illustrate the implications of the marginal effect and convert it to a welfare valuation in a more accessible way, we present calculations in Table 5 using both the unweighted LCNB and our preferred benchmark, weighted LCNB regressions. We develop three synthesized contingent scenarios: transformation of the park's nightlight to mean rural, suburban, and urban states, by averaging the homebase nightlight based on that experienced by visitors from each of those three homebase categories (Row 1 of Table 5). We then aggregate the marginal contingent behavior change and welfare value for each synthesized scenario.

Rows 3 and 4 of Table 5 show the days lost if the park's nightlight were as bright as the average rural, suburban, and urban night. Specifically, we use the formula $\Delta days = days_{\text{hist}} - \exp\Big(\gamma_{nl} \times (nl_{\text{cf}} - nl_{\text{park}})\Big)\, days_{\text{hist}}$, where $days_{\text{hist}}$ is the average historical visit days, nl_{cf} is the counterfactual synthesized nightlight, nl_{park} is the actual park nightlight, and γ_{nl} is the estimated regression coefficient for nl. Using the unweighted LCNB estimation, each visitor would reduce their days at the site in the next five years by 0.08 days, 0.65 days, and 1.19 days if the park night were to become as bright as the mean rural, suburban, and urban nightlight, respectively. With the weighted LCNB estimation, the reductions are 0.07 days, 0.60 days, and 1.12 days, respectively.

Rows 6 and 7 of Table 5 calculate the average consumer surplus loss for each synthesized contingent scenario. The unweighted LCNB estimates \$323.95 for consumer surplus per visitor per day at the park, while the weighted LCNB estimates \$1,226.29. We multiply the estimated consumer surplus per day by the visitation days lost due to increased light

Table 5: Estimates of losses in recreation days and consumer surplus from potential increase in nightlight pollution at the park.

	Synthesized scenarios		
	(1) Rural	(2) Suburban	(3) Urban
Average light	1.8173	15.3257	32.0768
Days lost per visitor in the next five years:			
LCNB	0.075	0.647	1.186
Weighted LCNB	0.069	0.602	1.115
Equivalent consumer surplus loss per visitor per year:			
LCNB	\$4.45 (3%)	\$39.02 (23%)	\$72.27 (42%)
Weighted LCNB	\$18.27 (3%)	\$158.66 (24%)	\$290.79 (44%)
Equivalent aggregate consumer surplus loss per year:			
LCNB	\$2,226,521	\$19,510,272	\$36,132,641
Weighted LCNB	\$9,137,341	\$79,330,106	\$145,395,875

Note: This table presents estimates from unweighted and weighted LCNB regressions under three synthesized nightlight scenarios (rural, suburban, urban). It reports the average synthesized nightlight levels, the estimated reduction in visitation days per visitor over five years, the corresponding annual consumer surplus loss per visitor, and the aggregate annual consumer surplus loss (assuming 500,000 visitors).

pollution and adjust the time frame to yearly to estimate the equivalent consumer surplus loss per year. On average, visitors incur a welfare loss valued at \$4.45, \$39.02, and \$72.27 per year using unweighted LCNB estimation, and \$18.27, \$158.66, and \$290.79 per year using the weighted LCNB, for park nightlight transformations to mean rural, suburban, and urban homebase nightlight, respectively.

To provide perspective on these monetary losses, we express them as percentage decreases relative to a baseline annual consumer surplus per visitor. For instance, using the unweighted LCNB for the suburban scenario: visitors averaged 2.68 visit days over five years, which equates to approximately 0.536 days per year (2.68 divided by 5). Multiplying the daily consumer surplus of \$323.95 (as reported in the previous section from Table 4) by 0.536 results in a baseline annual consumer surplus of \$173.64 per visitor. In the suburban scenario, the estimated annual loss amounts to \$39.02 per visitor, which represents about 22.5% (rounded to 23%, as shown in Table 5). Similar calculations indicate losses of approximately 3% for a transformation to a rural brightness and 42% for an urban brightness with the unweighted model, as well as 3%, 24%, and 44% with the weighted model, respectively.

Finally, we augment the individual visitor behavior and losses with total visitation numbers to calculate aggregate consumer surplus losses per year (Rows 9 and 10). In 2022, there were 493,428 total recreation visits to Great Sand Dunes National Park and Preserve (Flyr and Koontz, 2023). For estimation purposes, we conservatively assume that the baseline average number of total recreation visits to the park over the next five years would be 500,000 annually. For our site, a transformation to mean rural homebase nightlight seems to be the most plausible of the three scenarios in the immediate future. However, we include the suburban and urban scenarios for completeness and to show how losses would likely increase if the night sky became brighter. Additionally, these results may be useful in benefits transfer exercises for other relatively dark sites where a future shift to suburban or brighter night sky quality holds a higher probability.

5 Conclusion

This study estimates consumer surplus losses from potential increases in nightlight pollution at the Great Sand Dunes National Park and Preserve, a Gold Tier International Dark Sky Park. Using on-site interception surveys and the contingent behavior method, our analysis indicates that even modest increases in light pollution, comparable to nearby rural levels, would reduce visitation by 3% and lower consumer surplus. Larger increases would further decrease visitation, spending, and overall consumer surplus.

Places like the Great Sand Dunes have heavily invested in updated lighting, educational programs, and community partnerships to preserve their dark skies. Our analysis indicates that these investments generate substantial economic benefits. While the park's night sky is unlikely to reach the brightness of suburban or urban areas soon, our estimates suggest that consumer surplus losses could exceed 25% under those circumstances. As the first rigorous study of its kind, our findings may inform benefits-transfer exercises for other dark-sky sites with less protection from future light pollution. Overall, our study provides strong evidence that dark sky preservation enhances recreation and tourism and supports incorporating dark sky conservation into broader nature preservation strategies.

A substantial innovation in our research is measuring and presenting the quality of a site's dark sky and potential future changes in darkness to respondents. Dark sky quality is subjective, and the damage that nightlight pollution does is a continuous phenomenon. To make the concept accessible, we asked respondents to compare the night sky at the park to the night sky they experience at home. This creates a discrete and familiar scenario for each respondent and a synthetic continuous set of contingent nightlight pollution scenarios for the researcher. This method allows us to analyze a wide range of potential night sky conditions as a continuous variable. In other contingent behavior work of which we are aware, scenarios are discrete and typically few (often, one) in number.

Moreover, we use a combination of models to estimate baseline trip demand and consumer surplus, assess the impact of changes in nightlight pollution on visitor behavior, and evaluate the declines in consumer surplus caused by a brighter night sky. This combination of model approaches includes a combined revealed and stated preference negative binomial trip demand model, augmented by a fixed-effect panel approach estimated within a latent class framework, with checks for robustness concerning group-specific effects. Furthermore, the analysis incorporates inverse visit-day weights from Shi and Huang (2018). This combination of methods addresses on-site sampling issues, response heterogeneity, and the correlation among revealed and stated trip observations. The use of the inverse weights within a latent class framework in this context is new to our knowledge.

It is important to acknowledge possible omissions, biases, and uncertainties in our estimation of prospective changes in consumer surplus under brighter-sky scenarios. For instance, this analysis conservatively uses recent visitation levels at the park to scale per-visitor impacts and yield aggregate consumer surplus losses. Visitation numbers generally rise over time, driven by increases in population and income. Our contingent behavior scenario surveyed visitors regarding their anticipated changes in visiting habits over the next five years. Therefore, if one were to use projections of likely increased visitation in future years, the aggregate estimates of losses would be greater.

Another issue involves those who have not visited the park but might in the future because of its status as a Gold Tier International Dark Sky Park. These individuals may opt not to visit if the night sky were to become brighter in the future. Since our survey only polls park visitors, it does not provide direct information on the recreational preferences of those who have never been there. It is reasonable to assume that many people fall into this category. However, our analysis does not consider this group of potential future losses. Consequently, the estimates of losses in net consumer surplus are likely conservative, all else being equal.

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Appendix A Visitor Survey

We appreciate your time and feedback. Please fill in the blanks as appropriate. If any question makes you uncomfortable, feel free to skip it.

1. Visitor Origin (Home base, where you live for most of the year):

a. ZIP code: ____________________

b. City/Town: ____________________

c. State/Province: ____________________

d. Country: ____________________

e. Area type (please circle one): Urban / Suburban / Rural

2. Visitation Frequency and Duration:

a. Number of visits to *the Great Sand Dunes* in the past 5 years: ____________________

b. Average duration (in days) of each visit to *the Great Sand Dunes*: ____________________

c. Including yourself, how many people do you usually have in your immediate travel party? ______________

3. Demographics and Occupation:

a. Age: ____________________

b. Highest degree completed: ____________________

c. Current Occupation: ____________________

4. Budgeting:

a. Estimated average daily expenses during visit (e.g., on food, lodging, recreation, and any other expenses except the costs of traveling to and from *the Great Sand Dunes*): __________________

b. Estimated transportation expenses for round trip from your home base to *the Great Sand Dunes*: ____________________

5. Night Sky Observation:

a. Have you spent time looking at the sky or stars at night during your visits to *the Great Sand Dunes*? (please circle one): Yes / No

b. How would you rate the quality of the night sky/stars at *the Great Sand Dunes* on a scale of 1-10? (1 being poor, 10 being excellent): ______________

6. Future Plans Regarding Night Sky Quality:

The Great Sand Dunes is currently designated as an International Dark Skies area. Some people who visit here enjoy viewing the night sky because it is possible to see a larger number of stars than one may see at most other places. We would like to ask you a question about how you think you might change your visiting plans to this site (if at all) over the next 5 years if the nature of the night sky here were different than it is now.

6a. Specifically, if the night sky at *the Great Sand Dunes* looked identical to the sky at your home base *(where you live for most of the year)*, that is, you could see about the same amount of stars here as at your home base, do you think you would change your visiting plans *(that is, either the number of visits or the length of those visits)* to *the Great Sand Dunes* over the next 5 years? *Assume that, even if we had more or fewer stars to see at night at the Great Sand Dunes, the nature of the other amenities and qualities of the Great Sand Dunes would stay the same.*

(please circle one): Yes / No

If yes, how would your plans change? Would you plan to:

6b. Make either fewer or shorter visits to this site?: _______________ (Check if yes)

or:

6c. Make either more or longer visits to this site? ________________ (Check if yes)

If "yes" on **6b**, please specify:

6d. How many fewer visits over a 5-year period? ______ fewer visits

6e. How much shorter would your visits be on average? : ____ fewer days per visit

If "yes" on **6c**, please specify:

6f. How many more visits over a 5-year period? ______ more visits

6g. How much longer would your visits be on average? : ____ more days per visit

7. What is your annual household income (in US dollar)?

[ ] Below $25,000

[ ] 25,000 to 49,999

[ ] 50,000 to 74,999

[ ] 75,000 to 99,999

[ ] 100,000 to 149,999

[ ] 150,000 to 199,999

[ ] 200,000 to 249,999

[ ] Over 250,000

Thank you for your participation!