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Analysis

Incorporating local visitor valuation information into the design of new recreation sites in tropical forests

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A B S T R A C T

In rapidly industrializing countries, decisions need to be made as to what characteristics new tropical forest parks in or near urban areas should have. Using a discrete choice experiment, we estimate prospective visitors' willingness-to-pay for a range of forest park characteristics for a representative sample of Malaysian households in the Kuala Lumpur–Selangor region. To enable park managers to adapt park designs to important types of heterogeneity among park visitors, we further identify how these estimates vary across geography (i.e., residential location: urban, suburban, rural), major ethnic groups, and patterns of recreational behavior. We show how a model that includes a wide array of visitor heterogeneity can be used to identify configurations of park characteristics that maximize social welfare across both the general sample and specific subgroups of prospective visitors.

1. Introduction

With evidence that nature-based tourism is on the rise globally, concern that public support for conservation will wane as a result of people becoming detached from their natural environment can perhaps be tempered (Balmford et al., 2009). How to manage nature-based destinations in light of this trend continues to be an issue, however (Onofri and Nunes, 2013; Lindberg and Veisten, 2012; Juutinen et al., 2011; Jacobsen and Thorsen, 2010). The challenge is to find the appropriate mix of natural and built attributes of nature-based recreation sites, consistent with society's preferences across those attributes and recognizing that there may be significant heterogeneity in preferences across cultural, ethnic, and socioeconomic lines.

In the case of recreation sites in tropical forests, failure to identify the right mix of attributes can have serious consequences for the achievement of conservation, tourism, and economic development goals. For instance, efforts to entice forest owners and managers, who are often state or national governments in tropical countries, to set aside land for conservation frequently highlight tourism revenues as a replacement for logging revenues.[1] Failure to generate the expected revenues could result in forest parks losing their protected status. Similarly, excessive or poorly-planned tourism could threaten biodiversity within and around forested parks and, consequently, the sustainability of the parks for both conservation and tourism (Juutinen et al., 2011; Lindberg and Veisten, 2012).

The sustainability and success of forest parks depend on a number of related decisions by park managers that affect visitors' on-site experiences and welfare. First, park managers determine visitors' access to higher-valued natural attributes such as water bodies, waterfalls, scenic overlooks, and popular animal or plant populations. The potentially accessible set of natural site-specific attributes available to visitors is influenced not only by park siting decisions but also by the provision of on-site transportation infrastructure (e.g., trail and roadway designs) that gives visitors access to such natural features. Second, through decisions about the appropriate level of investment in on-site services and infrastructure, park managers determine levels of park attributes such as toilets, parking, lighting, picnic tables, and signage. Third, when formulating staffing plans, park managers determine the level of labor-dependent site attributes

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[1] Indeed, as suggested in Balmford et al. (2009), nature-based tourism can generate "substantial resources for both conservation and local economic development" (Balmford et al., 2009; p. 1). In Malaysia, the creation of Royal Belum State Park offers an example of ecotourism being advocated as an activity that could offset the loss of government revenue resulting from restrictions on logging (Schwabe et al., 2015).

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such as litter levels, personal security, and the availability of interpretative services. Finally, by understanding how congestion levels impact visitors' on-site experience and welfare, park managers may better regulate congestion through parking and entrance fee policies.[2]

Discrete choice experiments (DCEs) have been suggested as a tool to assist forest managers in making these decisions by providing better information on society's preferences for natural versus built attributes of forest parks (Lindberg and Veisten, 2012; Juutinen et al., 2011; Abildtrup et al., 2013; Jacobsen and Thorsen, 2010; Christie et al., 2007). This information is required if park managers are interested in maximizing the social value of tropical forests as recreational destinations in and near urban areas. It enables government agencies to invest in park infrastructure and manage park services in ways that attract prospective visitors and balance the cost of providing park attributes with the benefits visitors receive from those attributes.[3] And while management decisions can be complicated by the fact that prospective visitors come from diverse groups who may use and value parks in different ways, DCEs can be constructed so as to identify the preference heterogeneity across such diverse groups along with any differences in their values for site attributes such as natural amenities, on-site services, and infrastructure.

The current study uses survey-based data from Malaysia to illustrate how DCEs can be used to evaluate the design and value of a new tropical forest park intended to serve domestic, not foreign, users. It highlights how preferences for a new park differ across (i) the natural versus built attributes of the park and (ii) groups of prospective visitors. To our knowledge, this is the first such analysis in a developing country.[4] We also provide an extensive analysis of how the conclusions one may draw from the results of a DCE can be influenced by modeling strategy.

We estimate prospective visitors' marginal willingness-to-pay (WTP) for a comprehensive set of natural and built characteristics of a hypothetical new forest park in Peninsular Malaysia: 1) drinking water and toilets, 2) walking trails, 3) picnic tables and grills, 4) level of crowdedness, 5) litter, 6) likelihood of seeing birds and other wildlife, 6) access to a stream and small waterfall, and 7) the entrance fee. We obtained data for these analyses by conducting a DCE using a stratified random in-person survey of nearly 1300 households in more than 200 locations within the federal Capital Territory of Kuala Lumpur (KL) and the neighboring state of Selangor in 2010. This survey differed from prior environmental valuation surveys in developing countries by including rural, suburban, and urban households, with representation of all major ethnic groups (Bumiputera, Chinese and Indian),[5] which required four different language versions of the survey instrument (Malay, Chinese, Tamil, and English). The survey presented households with choice sets containing alternative park-attribute scenarios, plus the option to choose neither alternative.

Malaysia is an instructive case study because it is representative of the many forest-rich, middle-income countries with rapidly urbanizing populations comprised of diverse ethnic groups.[6] We explore how these estimates of WTP for site attributes vary with the residential location, ethnicity, and past recreational behaviors of prospective visitors. Our model encompasses many additional visitor characteristics (e.g., income, gender, age, and household size) which we use to identify the configuration of park attributes that maximizes the public's WTP for access to the park. We show how this model can identify the optimal configuration of park attributes for diverse groupings of visitors as well as for a nationally representative sample.

2. Relationship to Existing Literature

There are several distinct literatures that are relevant to our study and to which our study contributes. Our analysis is distinctive in that it evaluates WTP for alternative aspects of managed and natural site quality for a new park that will be visited by culturally distinct segments of the population. Most previous stated-preference studies on the recreational value of tropical forests have employed contingent valuation to value access to an existing site or to value creation of a new site with a fixed set of characteristics in a specific location (Loomis and Walsh, 1997; Chase et al., 1998; Mladenov et al., 2007; Samdin, 2008).[7] DCEs have been applied to the valuation of goods and services from tropical forests (Rolfe et al., 2000; Othman and Bennett, 2004; Barkmann et al., 2008; Gelo and Koch, 2012; Vincent et al., 2014), but they have generally not focused on recreation.[8] Two exceptions are DeShazo and Fermo (2002) and Naidoo and Adamowicz (2005), which both estimated the recreational value of site attributes in a tropical forest park. However, they focused on producing estimates that would support park design and management decisions at existing parks, not new ones, and they did not investigate how preferences varied with local domestic visitor characteristics.

We also characterize differences across visitors' valuation of park attributes in a distinctive way for this literature. Prior studies have explored variation in preferences for different park configurations by asking respondents for an assessment of the importance of specific attributes on a numeric rating scale (Li et al., 2010).[9] In contrast, we use two approaches to investigate the role of heterogeneity in modeling consumer choice behavior: the popular mixed (random parameters) logit model that allows for (and estimates) a distribution of preferences over the attributes of a new park configuration (Train, 2009), and a conditional logit model, which is fully parameterized with a set of interactions between the park attributes and respondent characteristics.[10] Except for income and past trip behavior, there has been relatively little economics research exploring the influence of respondent characteristics, particularly

[2] Visitors may be negatively or positively impacted by congestion depending on their preferences for social engagement or solitude.

[3] Balmford et al. (2009; p. 4) similarly emphasize that nature-based tourism is only likely to be sustainable with local participation and effective planning and management.

[4] Jacobsen and Thorsen (2010) was evidently the first study to use DCEs to evaluate the design and site designation of a new national park, albeit in a developed country.

[5] In our analyses, we follow the Malaysian Department of Statistics' division of households into three ethnic categories: Bumiputera, Chinese, and Indian, where Bumiputera includes Malays, Orang Asli, and other groups classified as indigenous by the federal government.

[6] Middle-income countries with significant tropical forests include Angola, Botswana, Brazil, Colombia, Costa Rica, Cuba, Ecuador, Gabon, Mexico, Namibia, Panama, Peru, Suriname, Thailand, and Venezuela.

[7] Four studies that have used DCEs for forest park design in developed countries include Lindberg and Veisten (2012); Juutinen et al. (2011); Abildtrup et al. (2013), and Jacobsen and Thorsen (2010). Lindberg and Veisten (2012) evaluated how the preferences of local and non-local residents in Norway for the development of a gondola (along with other built-system attributes) adjacent to a national forest were influenced by perceived impacts on wild reindeer habitat (the natural system). Juutinen et al. (2011) focus on understanding tourist preference heterogeneity for attributes that influence biodiversity and recreational services of a national park in Finland. Abildtrup et al. (2013) focus on estimating the recreational user preferences for both built and natural system attributes within forests in Northeastern France, as well as identifying the determinants of preference heterogeneity. Jacobsen and Thorsen (2010) use a mail questionnaire within Denmark and find that preferences for different forest sites within Denmark and their attributes are largely influenced by cultural and regional views suggesting caution surrounding inclinations to transfer the results from one study site to another policy site.

[8] Gelo and Koch (2012), for instance, use a DCE to value different elements of a community forest program. Their study focuses on the productive elements of the tropical forest for agricultural and nontimber forest collection rather than on a forest park for recreation.

[9] The drawback of this rating approach is that different groups may use rating scales in different ways; also, rating scales do not force respondents to make actual choices between alternatives (Lee et al., 2007).

[10] Mogas et al. (2006) compare estimates of the total value of afforestation programs in Spain using a single binary discrete choice question versus a more complex DCE using a sequence of multinomial choice questions, which allows explicit attributes to be valued. They found no statistically significant difference between the two approaches after interaction terms between the attributes were included in their model.

ethnicity, although there is a more extensive literature on the sociology of outdoor recreation that looks at this issue.[11]

Finally, the sample to which we administer this survey is representative of national citizens rather than foreigners, who have often been the focus of recreation demand studies in developing countries. In addition, our survey implements an unusually rigorous sampling plan with the stratification and cluster design typical of large-scale, high-quality, in-person surveys and up to three call-back attempts to interview respondents for whom initial efforts to obtain a completed interview were not successful.[12] These two features of the survey affect our choice of estimation strategies in important ways. First, to accommodate clustering within our sample we need to employ corrective weighting in our final model. Second, the presence of up to three callbacks to respondents represents another possible source of heterogeneity that we control for in our most inclusive model.

3. Discrete Choice Experiment (DCE) Overview

3.1. Household Survey

We conducted a stratified random in-person survey of nearly 1300 households in more than 200 locations within the federal Capital Territory of KL and the neighboring state of Selangor in 2010. The survey included three strata—KL (100% urban), urban Selangor, and rural Selangor—with representation of all major ethnic groups. An overview of the survey can be found in Vincent et al. (2014), "Materials and Method"; for details on survey design and implementation, see DeShazo et al. (2015).

3.2. New Park Scenario and Payment Vehicle

The survey instrument included multiple valuation modules. Our concern in this paper is just with the module for a new forest recreation park. In that module, we presented respondents with a scenario in which the government plans to open a new park. The text, read to them by an enumerator, is:

> "How much you enjoy a forested park can depend upon the services at the park. Park services include things like well-maintained trails, picnic facilities, water and toilets, and other amenities. The government needs information on what services are important to you. I want you to think about the possibility that the government will open a new forested park. A small river would flow through the park. The government must decide which services and amenities to provide at this park. Assume that this park will be located within a 2-hour drive of your home so you could visit it and return home within a single day."

This description establishes that the park would be used for day-trips, not overnight trips. Allowing for overnight trips would require a more complex choice design. The text also establishes another feature of the park common across all plans: a small river would flow through it.

The payment vehicle takes the form of an entrance fee that would be paid per adult, per visit to the site. We motivate this payment vehicle as follows:

> "The new park might offer many different kinds of services and amenities. On the next page we are going to show you different plans (A and B) for the new park. Both plans will include a well-lit and secure parking lot. The costs of these plans differ because they provide different levels of services. To cover costs, entrance fees will be charged for each adult. Parking is free with admission."

Table 1
Attributes and attribute levels for the proposed park.

Attributes of proposed park	Levels
Fee	2, 5, 10, 15ringgit (RM)
Toilet	0—No 1—Yes
Trail	0—Dirt/gravel 1—Paved
Picnic	0—No 1—Yes
NoCrowd	0—Crowded 1—Few people
NoLitter	0—Litter noticeable 1—Not noticeable
Birds	0—Rarely seen 1—Frequently seen
Stream	0—Not accessible 1—Easy access
Info	0—No 1—Yes

In addition to providing a rationale for the payment vehicle and explaining why it varies across park plans, this text introduces another park feature common to all plans: parking is available in a well-lit and secure lot with admission. Participants in focus groups and cognitive interviews expressed reluctance to visit any park that did not provide safe parking.

3.3. Choice Setting and Park Attributes

We then briefly presented and reviewed the nine attributes that would characterize each new park configuration, as shown in Table 1.[13] The entrance fee (*Fee*) variable takes on one of four levels (2, 5, 10, 15 Malaysian ringgits, or RM).[14] The other eight attributes are all binary. The variable *Toilet*, indicating the presence of toilets and drinking water, takes on a value of one if available and zero otherwise. The variable *Trail* takes on a value of zero for dirt walking trails and one for paved trails, while *Picnic* equaling one indicates the presence of picnic tables and grills while a value of zero indicates their absence. The variable *NoCrowd* takes on a value of one to indicate that few other people are present at the site while a value of zero indicates that many people are present. The *NoLitter* variable equals one for no noticeable presence of litter while a value of zero indicates the presence of noticeable litter. If birds and other wildlife are always seen, the variable *Birds* takes on a value of one; if they are rarely seen, the variable is assigned a zero. If there is easy access to a stream or waterfall, *Stream* takes on a value of one and if there is no (easy) access, then *Stream* takes on a value of zero. *Info* is equal to one if visitor information is provided and zero if it is not.

Each of the DCEs involved a set of three alternatives: two different new park configurations, and the option of indicating that respondents would not want to visit either of the configurations. In the case of choosing "neither park," the implied attributes for our choice model are mostly obvious. The values for *Fee*, *Toilet*, *Trail*, *Picnic*, *Birds*, *Stream* and *Info* are all assumed to be equal to zero. The level of *NoCrowd* and *NoLitter* are more uncertain. In the absence of a formal parking situation, we have assumed that *NoCrowd* is also equal to zero. *NoLitter* could plausibly be defined either way but we have chosen here to go with the traditional coding of making NoLitter equal to zero for the "neither park"

[11] There has been a limited amount of work by economists on the role of ethnicity (e.g., Bowker and Leeworthy, 1998; Johnson and Bowker, 1999; Loomis et al., 2006; Hoyos et al., 2009; Zander and Straton, 2010), although there is considerably more work by sociologists on preferences and differences in recreational use patterns (e.g., Carr and Williams, 1993; Winter et al., 2004). Our emphasis here is on differences in choice behavior with respect to a set of park attributes.

[12] Standard references on dealing with complex survey designs include Cochran (1977) and Levy and Lemeshow (2008).

[13] An example show card displaying the two park configuration alternatives can be found in Appendix 1.

[14] At the time the survey was undertaken in 2010, one Malaysian ringgit (RM) was worth $0.31 U.S. dollars.

Table 2
Parameter estimates from alternative logit modeling approaches.

	Simple conditional	Conditional with weights	Mixed uncorrelated	Mixed correlated
Fee	−0.08***	−0.07***	−0.17***	−0.16***
	(0.000)	(0.000)	(0.000)	(0.000)
Toilet	1.03***	0.83***	2.45***	2.54***
	(0.000)	(0.000)	(0.000)	(0.000)
Trail	0.05	0.07	0.20	0.32**
	(0.374)	(0.391)	(0.129)	(0.023)
Picnic	0.28***	0.23**	0.61***	0.77***
	(0.000)	(0.013)	(0.000)	(0.000)
NoCrowd	−0.03	0.01	−0.03	−0.02
	(0.632)	(0.936)	(0.859)	(0.923)
NoLitter	0.28***	0.21**	0.59***	0.66***
	(0.000)	(0.012)	(0.000)	(0.000)
Birds	0.38***	0.39***	0.85***	0.98***
	(0.000)	(0.000)	(0.000)	(0.000)
Stream	0.39***	0.53***	0.85***	0.86***
	(0.000)	(0.000)	(0.000)	(0.000)
Info	0.39***	0.39***	0.81***	0.85***
	(0.000)	(0.000)	(0.000)	(0.000)
Standard deviations				
Toilet			2.41***	2.55***
			(0.000)	(0.000)
Trail			1.44***	0.89***
			(0.000)	(0.002)
Picnic			1.59***	1.15***
			(0.000)	(0.000)
NoCrowd			−2.22***	2.30***
			(0.000)	(0.000)
NoLitter			−1.51***	1.82***
			(0.000)	(0.000)
Birds			1.74***	1.65***
			(0.000)	(0.000)
Stream			1.71***	1.68***
			(0.000)	(0.000)
Info			2.27***	2.22***
			(0.000)	(0.000)
N	7566	7566	7566	7566
chi2	689.83		194.03	287.04
ll	−2425.78		−2328.77	−2282.26

p-values in parentheses. Exchange rate is US\$1 = RM 3.22 (2010).
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

alternative. Each respondent was presented with, in sequence, four different DCEs (i.e., four sets of two different park configurations).

4. Results: Conditional Logit and Mixed Logit Models

4.1. Unweighted Conditional Logit Model

Based on the data generated from the respondents' choices, we first estimated the usual benchmark, a conditional logit model without spatial clustering, which is shown in Table 2. We had strong prior hypotheses for seven of the nine variables: *Fee* should have a negative coefficient; *Toilet*, *Picnic*, *NoLitter*, *Birds*, *Stream* and *Info* should have positive coefficients. These expectations are supported by the evidence, as all of these parameter estimates are highly significant ($p < .001$). The two variables for which we had no expectations—*Trail* and *NoCrowd*—are both statistically insignificant. Below, we explore whether this is because respondents do not care about these attributes, or if the preferences of one sub-sample for an attribute level are effectively canceled out by the preferences of another sub-sample for the opposite level.

WTP in the form of a higher entrance fee for the new park is calculated as the ratio of the parameter on the attribute of interest divided by the negative of the parameter on *Fee*. For instance, WTP for moving from *Toilet* equals zero to *Toilet* equals one, can be found by dividing the coefficient on *Toilet*, 1.03, by the negative of the coefficient on *Fee*, −0.08, which yields an estimate of RM 13.06. Because this calculation involves the ratio of two normally distributed parameter estimates, we use a bootstrap approach to obtain a confidence interval for it and other WTP calculations.

Our WTP results (see Table 3) seem sensible. Our sample, taken as a whole, cares strongly about whether a park has drinking water and toilet facilities.[15] The two attributes for which we did not have clear prior expectations are both insignificantly different from zero: the parameter on *Trail* yields a WTP estimate of RM 0.65, while WTP for *NoCrowd* was negative RM 0.39.

If the conditional logit model is an adequate representation of preferences, then it is easy to identify the most preferred park configuration that maximizes consumer surplus. For the sake of simplicity, we assume that the cost of supplying the attributes is zero (this assumption could be modified if actual costs were known). The most preferred park configuration, which maximizes consumer surplus, can be identified by the attribute levels indicated by the sign on the non-*Fee* coefficients. The most preferred park configuration that maximizes consumer surplus has the following configuration: toilets/drinking water, paved trails, picnic tables/grills, is designed so other people are frequently seen, does not have noticeable litter, is located where birds/wildlife are frequently seen, has easy access to streams/waterfalls and supplies visitor information about the park. Total WTP for this park configuration has an entrance fee of RM 35.61. We calculate this total WTP as the sum of the park attributes times their respective coefficients divided by the negative of the coefficient on *Fee*, under the frequently made assumption of no income effects influencing demand.[16]

4.2. Weighted Conditional Logit Model

In our next model, we employ a correction for the spatial clustering of our sample by weighting the likelihood function using Stata's (StataCorp, 2011a) svy: prefix operator. We expect this correction to have two effects on the previous results. First, it increases the weights on KL respondents relative to those from rural Selangor to compensate for differences in the sampling intensities and response rates across the strata, and it increases the weight on respondents of Chinese ethnicity and some household sizes as a result of post-stratification adjustments. These adjustments may change the magnitude of parameter estimates if there are systematic differences in preferences along these dimensions. Second, the svy: weighting will inflate confidence intervals/reduce z-statistics to reflect the cluster aspect of our sampling design under the assumption that respondents in the same cluster are more likely to share common unobservable characteristics than would a simple random sample of respondents. The effect of this clustering assumption is to produce substantially larger standard error estimates by considerably reducing the effective sample size. It tends to be accurate when respondents are sampled in very close proximity, such as a small village, but is somewhat conservative (i.e., might underestimate significance) when the clusters are defined over a larger spatial area such as ours.

[15] It is possible to look at whether there is a positive or negative status quo effect by including a variable representing the attribute levels of the "neither park" configuration in the conditional logit model. A likelihood ratio test for whether this variable needs to be included yields a test statistic of 0.7314, which has a chi-square (df = 1) distribution and a p-value of 0.392. Note that the status quo effect here is only statistically identified if *Fee* is entered as a continuous variable in the model.

[16] For the conditional logit model, the representative agent's mean and median WTP are equal. With the assumption that the error distribution is symmetric, this translates into half of the households having a WTP of more than RM 35.61 and half having a lower WTP. The more complex models we estimate later relax the assumption that all households have the same preferences up to a symmetric random error component in different ways, leading to a richer picture of the distribution of WTP in the sample. The different levels of the park attributes have different supply costs, so aggregate WTP estimates for a particular configuration of the park should be done after netting out cost. The specific location of the park will matter. When positive entrance fees are charged, one also has to forecast visitation rates, and there is a clear tradeoff between the magnitude of the entrance fee charged and visitation rates, which creates complications when a government agency wants to maximize both (Teasley et al., 1994).

Table 3
WTP values for attributes under alternative logit model specifications (RM)*.

Attribute		Simple conditional	Mixed uncorrelated	Mixed correlated
Toilet	*Mean*	13.06	14.42	15.57
	Lower bound	10.85	11.94	12.65
	Upper bound	15.26	16.90	18.50
Trail	*Mean*	0.65	1.19	1.99
	Lower bound	(0.78)	(0.32)	0.37
	Upper bound	2.08	2.70	3.62
Picnic	*Mean*	3.51	3.61	4.70
	Lower bound	1.94	1.95	2.75
	Upper bound	5.07	5.27	6.66
NoCrowd	*Mean*	(0.39)	(0.15)	(0.09)
	Lower bound	(1.98)	(1.80)	(1.96)
	Upper bound	1.20	1.50	1.77
NoLitter	*Mean*	3.58	3.46	4.04
	Lower bound	1.96	1.81	2.11
	Upper bound	5.19	5.11	5.97
Birds	*Mean*	4.87	5.00	6.04
	Lower bound	3.35	3.47	4.37
	Upper bound	6.40	6.55	7.72
Stream	*Mean*	4.99	4.99	5.27
	Lower bound	3.37	3.56	3.00
	Upper bound	6.60	6.62	7.53
Info	*Mean*	4.95	4.75	5.24
	Lower bound	3.47	3.13	3.44
	Upper bound	6.44	6.36	7.04

* Lower and upper bound estimates refer to the 95% CI generated using the Delta method.

Considering the conditional logit alongside the corrected-weights logit, we observe three major differences by comparing columns 2 and 3 in Table 2. First, all of the p-values in column 3 are at least as large if not considerably larger than those in column 2, a result of the standard errors in column 3 being considerably larger than those in column 2. All the attributes that were significant at 5% or better in column 2, though, are still significant in column 3. Second, the coefficient on *Fee* has fallen, suggesting that after applying the complex survey design weights, our representative agent is somewhat less price sensitive. All else being equal, this will produce larger WTP estimates.

The coefficients on the park configuration attributes have also changed, which has implications for calculations of WTP as it is a ratio estimator. The WTP calculation for *Toilet* now yields RM 12.70 versus RM 13.06 from the unweighted column 2 model. This is a small difference with little economic meaning and is not statistically significant.[17] WTP for the other attributes are: *Trail* RM 1.01, *Picnic* RM 3.60, *NoCrowd* negative RM 0.10, *NoLitter* RM 3.19, *Birds* RM 6.02, *Stream* RM 8.09, and *Info* RM 5.95. The estimates for *Trail*, *NoCrowd*, and *NoLitter* are not statistically or economically different than their unweighted counterparts, even though *NoCrowd* has changed its sign from being marginally negative to being marginally positive. WTP for two of the other three attributes—*Birds* RM 6.02 vs. RM 4.87 and *Info* RM 5.95 vs. RM 4.95—have increased just enough to potentially be economically significant. For the third variable, *Stream*, the increase in WTP (from RM 4.99 to RM 8.09) is large enough to be economically significant.

4.3. Mixed Logit Models

The mixed logit approach enables us to test for the presence of significant heterogeneity among respondents' preferences. It assumes that different respondents have different preference parameters that are randomly distributed, typically normally, around a central tendency. We display the results of this model in column 3 of Table 2. All of the park configuration variables are assumed to be normally distributed except for *Fee*, which is assumed to be a "fixed" parameter to avoid well-known problems that can occur if this variable is assumed to have a normal distribution (Revelt and Train, 1998).

A comparison of the log-likelihood for this model (−2328.77) with that of the basic conditional logit model in column 2 (−2425.78) suggests a much improved fit for the addition of eight extra standard deviation parameters (i.e., the likelihood ratio test statistic is 194.03, which has a chi-square (df = 8) distribution and a p-value <0.001). In addition, all of the standard deviation parameter estimates are highly significant (p-values <0.001), suggesting substantial heterogeneity with respect to all the park configuration variables, including *Trail* and *NoCrowd*. Note that *Trail* and *NoCrowd* have mean parameter estimates that are insignificant at the 10% level, even though the estimates of the standard deviation parameters are highly significant. The large standard deviation estimates for these parameters suggest that respondents care about these two attributes, but they disagree in such a manner that they are roughly balanced in the sample. Finally, the mean coefficients on the park configuration variables and on the parameter estimate for *Fee* are larger than those in the simple conditional logit model in column 2.

What matters here in terms of valuing forest park attributes, though, is the ratio of the park configuration variables to the *Fee* variable. Evaluating marginal WTP at the mean of each park configuration variable (note that the standard deviation estimates imply a distribution of marginal WTP estimates), we obtain the following WTP estimates: *Toilet* RM 14.42, *Trail* RM 1.19, *Picnic* RM 3.61, *NoCrowd* negative RM 0.15, *NoLitter* RM 3.46, *Birds* RM 5.01, *Stream* RM 4.99, and *Info* RM 4.75. Some, but not all, of these estimates are higher than the values estimated with the simple conditional logit model in column 2 (e.g., the WTP estimate for *Toilet* is 11% higher), and they provide an indication that WTP estimates are likely to increase with a more accurate representation of the preference heterogeneity in the data.

Indeed, estimation of a more flexible mixed logit model (last column of Table 2) that allows all of the park configuration variables to be correlated generates a further increase in estimated WTP of about 10%.[18] As shown in Table 3, which presents the WTP estimates for both the uncorrelated and correlated parameters mixed logit models along with their 95% confidence intervals,[19] the WTP estimates for the correlated model are greater in absolute value than for their uncorrelated counterparts. The simple conditional logit estimates, which are provided for comparison purposes, are typically a bit lower than the uncorrelated mixed logit estimates, which are in turn generally lower than the correlated mixed logit model estimates. Clearly, the correlated mixed logit model provides a better fit, and it passes a likelihood ratio test for inclusion of the extra variables.

5. Results: Targeted Exploration of Respondent Heterogeneity

Despite the ability of mixed logit models to document the presence of heterogeneous preferences, they do exhibit two major drawbacks. First, there is not a version of the mixed logit currently available that adequately handles complex survey weights due to the way these weights interact with the parameter covariance matrix, and second, nothing specific is learned about what types of people in the sample have what sorts of preferences. One way of identifying the extent to which different groups of people have different preferences is to estimate a simple main-effects conditional logit model for different subsamples. Another approach is to explicitly model interactions between respondent characteristics and attribute levels in the context of the standard conditional logit model. It is important to note that respondent characteristics cannot enter directly as predictors into the estimation as they

[17] Tests of statistical significance across these estimates are available from the authors upon request.

[18] The lower triangular covariance matrix for the mixed logit model with fully correlated parameters is provided in Online Appendix Table 2o.

[19] Confidence intervals for parameter estimates are calculated using the Delta method, while confidence intervals for WTP estimates are calculated using a bootstrap method. We use the bootstrap command in StataCorp (2011b) and use 100 replications, which should allow for reasonable normally distributed confidence intervals.

Table 4
Willingness-to-pay by geographic strata, ethnicity, and past recreation behavior (RM).

	Base	Geographic strata			Ethnicity			Past recreation behavior	
		Urban	Suburban	Rural	Bumiputera	Chinese	Indian	Trip	NoTrip
Toilet	13.06***	14.30***	11.18***	13.79***	13.95***	10.95	10.90***	13.96***	12.07***
	[10.53, 15.58]	[4.93, 23.68]	[7.41, 14.94]	[10.13, 17.44]	[10.77, 17.13]	[−23.42, 45,32]	[7.24, 14.57]	[9.99, 17.93]	[9.00, 15.13]
Trail	0.65	1.49	1.47	−0.65	−0.19	2.34	2.11	1.96**	−0.81
	[−0.96, 2.26]	[−2.03, 5.01]	[−1.44, 4.38]	[−3.10, 1.79]	[−1.88, 1.50]	[−3.27, 7.94]	[−0.59, 4.81]	[0.03, 3.90]	[−2.91, 1.29]
Picnic	3.51***	6.95***	2.81*	2.55*	3.90***	3.99	2.38	4.94***	1.85*
	[1.88, 5.14]	[1.72, 12.19]	[−0.14, 5.76]	[−0.26, 5.35]	[1.75, 6.06]	[−11.99, 19.97]	[−1.29, 6.04]	[2.12, 7.77]	[−0.04, 3.73]
NoCrowd	−0.39	2.04	0.10	−2.08*	−0.40	−2.20	0.92	0.13	−1.08
	[−2.10, 1.32]	[−1.69, 5.77]	[−2.94, 3.15]	[−4.17, 0.01]	[−2.27, 1.48]	[−10.80, 6.41]	[−2.97, 4.81]	[−2.58, 2.84]	[−3.13, 0.98]
NoLitter	3.58***	6.57**	1.50	3.82**	3.28***	8.96	0.90	3.44**	3.75***
	[1.92, 5.23]	[0.89, 12.24]	[−1.20, 4.19]	[0.90, 6.74]	[1.15, 5.40]	[−10.66, 28.58]	[−1.79, 3.59]	[0.49, 6.38]	[1.70, 5.81]
Birds	4.87***	4.06*	6.03***	4.20***	4.97***	3.63	5.81***	5.30***	4.37***
	[3.13, 6.62]	[−0.55, 8.68]	[2.63, 9.43]	[1.51, 6.90]	[2.56, 7.38]	[−4.36, 11.62]	[2.64, 8.98]	[2.14, 8.47]	[2.06, 6.68]
Stream	4.99***	5.75**	6.94***	3.02*	4.23***	8.80	5.04***	6.39***	3.48***
	[2.89, 7.09]	[1.23, 10.27]	[3.33, 10.55]	[−0.22, 6.25]	[1.96, 6.50]	[−12.44, 30.05]	[1.27, 8.82]	[3.45, 9.32]	[1.30, 5.66]
Info	4.95***	7.33***	5.78***	2.96***	4.17***	8.35*	5.28***	5.68***	4.18***
	[3.11, 6.79]	[2.36, 12.30]	[1.81, 9.75]	[0.82, 5.11]	[2.13, 6.20]	[−0.58, 17.29]	[2.01, 8.55]	[2.59, 8.78]	[2.30, 6.07]
N	7566	1830	2784	2952	5052	1482	1032	4518	3048

95% confidence intervals in brackets. Exchange rate is US$1 = RM 3.22 (2010).
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

do not differ across choice alternatives (i.e., plans, in our case) faced by the respondent; hence, if entered directly, they drop out.

We apply the former approach in this section, using it to explore three aspects of respondent heterogeneity:

- Do household preferences differ depending on whether the household is located in an urban, suburban, or rural environment?
- How do preferences differ depending on the reported ethnicity of the household?
- How do preferences differ depending on whether the household was known to take a recreation trip in the previous year or not?

Each of these questions is addressed individually through (1) comparing the statistical significance and sign of the attributes and model fit using a simple conditional logit for the entire sample versus various subsamples, and (2) comparing marginal WTP for each attribute for the whole sample versus the subsample estimates.

5.1. Preferences Across Geographic Strata

Table 4 presents results in terms of marginal WTP for different attributes. It illustrates how preferences differ depending on the characteristics of the households, with column 2 presenting the baseline conditional logit WTP estimates for the entire sample (the same as in Table 3). Columns 3 to 5 in Table 4 show how preferences differ based on whether the household was located in the metropolitan center of KL proper; the urbanized areas of Selangor, which are less dense and mostly adjacent to KL and which we term "suburban"; or the rural areas of Selangor.[20] A noticeable difference is that the subsample from KL has WTP values that are greater than the sample averages in every category except for *Birds*. For those values that are shown to be statistically significant, urban households have values for *Picnic* that are twice the sample values (RM 6.95 vs. RM 3.51). Comparing with other strata, we see that urban households have values for *Picnic* and *Info* that are 172% and 142% greater than those values from rural households. Urban dwellers also have strong preferences for cleaner parks compared to the rural and suburban households, as measured by the differences in WTP for *NoLitter*. A likelihood ratio test rejects the hypothesis of no geographic-related preference heterogeneity at $p = 0.01$.

5.2. Preferences Across Major Ethnic Groups

Columns 6 to 8 in Table 4 illustrate how preferences in terms of WTP for attributes differ across the three major ethnic groups in Malaysia: Bumiputera, Chinese, and Indian.[21] As shown, there are significant differences in the magnitude of the WTP values across ethnic groups with respect to their values for many of the attributes (e.g., *Toilet*, *Trail*, *NoCrowd*, *NoLitter*, *Streams*, and *Info*), but the differences for other variables tend not to be statistically significant. Substantial differences in attribute values across ethnic groups for statistically significant results show up in the *Info* variable, where the Bumiputera's WTP values are around RM 4.17 whereas the Chinese values are nearly double at RM 8.35 (although the confidence interval on this estimate is quite large, ranging from negative RM 0.58 to positive RM 17.29). Bumiputeras are shown to have the highest WTP values for *Toilets* (RM 13.95), whereas Indians have the highest values for *Birds* (RM 5.81). In general, these results show that the three ethnic groups largely agree with respect to the signs of their WTP estimates for the attributes but vary in their magnitudes. Further, neither *Trails* nor *NoCrowd* are statistically significant across any of the ethnic groups. All of this suggests that there may be substantial preference heterogeneity across ethnic groups, which is something that can be tested within a more comprehensive model that incorporates numerous interaction effects.

5.3. Preferences Conditional on Past Recreational Activity

Columns 9 and 10 in Table 4 provide the results of an analysis of whether preferences, expressed in WTP, for the attributes of a new forested park differ for households that reported having taken a trip to some forest or outdoor recreation park over the past 12 months

[20] Online Appendix Table 4o (columns 3–5) presents the conditional logit parameter estimates that produce the marginal WTP estimates by strata in Table 4. A likelihood ratio test rejects the hypothesis that the coefficients are the same across these three strata.

[21] Online Appendix Table 4o (columns 6–8) presents the conditional logit parameter estimates that produce the marginal WTP estimates by ethnicity in Table 4. A likelihood ratio test rejects the hypothesis that the coefficients are the same across these three subsamples. One of the main drivers of differences in this table comes from the coefficient on *Fee* for ethnic Chinese, in absolute value terms, being about 40% less than the sample average and while for Indians the absolute value of the *Fee* coefficient is almost 40% greater, suggesting Indians are, on average, much more price sensitive than the Chinese.

Table 5
Variables related to respondent characteristics and attitudes from survey questionnaire.

Variable abbreviation	Descriptions/levels
Respondent/household characteristics	
Age	Age of respondent
Income	Monthly income of household
HHsize	# of people living at residence
EthnicRecode	Ethnicity reported by the respondent (1—Malay; 2—Chinese; 3—Indian; 4—Other)
Gender	Gender of respondent (1—male; 2—female)
Children	Number of children in household
Childplace	Type of location respondent lived as a child (1—rural area; 2—small town; 3—city/suburb)
Job	Type of job respondent holds (1—management; 2—large business owner; 3—small business owner; 4—specialist/professional; 5—clerical; 6—factory worker; 7—farmer/agricultural worker; 8—unemployed; 9—don't work; 10—others
Strata	Type of location respondent currently resides (city; suburban; rural/small town)
Visited_AnyExclSlangor	
TripOverseas	Whether respondent took a trip outside Peninsular Malaysia in the past 12 months (1—yes; 2—no)
Visited_AnyState	Did respondent take a recreation trip to any state within Peninsular Malaysia
Edu	Highest level of education reached by respondent (1—no formal education; 2—completed primary education; 3—completed junior high school; 4—completed senior high school; 5—certificate holder; 6—diploma; 7—bachelor's degree; 8—master's or graduate degree)
TotalTrips_AllStates	Total number of trips to recreation areas in past 12 months throughout Peninsular Malaysia
Attitudinal responses	
EconVsEnv	Should government place a higher priority on economic development or protecting the environment (1—economic development; 2—environment)
Envist	Does respondent consider him/herself an environmentalist (1—yes, strongly; 2—yes, somewhat; 3—no; 4—not sure)
Timber	Importance of timber industry to the overall Malaysian economy (1—very important; 2—important; 3—somewhat important; 4—not very important)
Enumerator responses	
Attempt	Number of attempts to reach respondent, ranging from 1 to 3.
Attentive	Enumerator's judgment of the attentiveness of the respondent (1—not very attentive; 2—somewhat attentive; 3—very attentive)
IntLength	Length of the Interview (minutes)
SurveyLang	Language in which the interview was given (1—English; 2—Mandarin; 3—Malay; 4—Other)

compared to households reporting no such trip.[22] Such a comparison can be useful to better understand how a sample taken from a revealed preference on-site survey might have fared in representing preferences for forested parks relative to those of the general public. In looking at Table 6, we see that while *Toilets* are the attribute with the highest WTP values of between RM 12 to RM 14, the WTP values for households that took a trip are around 15% higher than those that did not take a trip. For the *Picnic* attribute, though, those that have taken trips are willing to pay around 167% more than those that did not take a trip, although the absolute difference is only around RM 3 per visit. Those that have taken trips also have significantly higher WTP values for *Info* (RM 5.68 vs. RM 4.18), *Streams* (RM 5.68 vs. RM 3.48), and *Birds* (RM 5.30 vs. RM 4.37). The only attribute with a statistically significant value that is larger for those that have not taken a trip is *NoLitter* (RM 3.75 vs. RM 3.44). A likelihood ratio test of parameter equality across these two subsamples is rejected, suggesting that those that have taken trips in the past have different preferences than those that have not.

5.4. Additional Sources of Household and Survey Design Heterogeneity

We also explored four other sources of heterogeneity in our sample which space limitations will not permit us to present. The first of these is the respondent's gender, where we found some statistically significant and economically interesting differences: e.g., female respondents seem to have stronger preferences for toilets and drinking water, while male respondents have stronger preferences for paved trails. For the other three variables—income (split into three groups), interview language, and number of interview attempts undertaken before a successful interview—parameter differences were fairly small and not statistically significant overall using a likelihood ratio test.

[22] Online Appendix Table 4o (columns 9–10) presents the conditional logit parameter estimates that produce the marginal WTP estimates across these subsamples in Table 4. A likelihood ratio test rejects the hypothesis that the coefficients are the same across these two subsamples.

6. Results: Fully Parameterized Conditional Logit Model

The approach presented next can be seen as an effort to accommodate measureable respondent heterogeneity by developing a conditional logit model that is fully parameterized in terms of interactions while still being parsimonious in terms of the number of parameters estimated. This approach involves excluding terms that are clearly statistically insignificant, even when using a liberal criterion for statistical significance that does not take account of our specification search. As before, our modeling strategy is to begin with an unweighted model, which we will then compare to a model that incorporates complex weighting to account for cluster sampling. We will then use this latter model to identify the top-ten park configurations as determined by our respondents' maximal WTP across the 256 possible park configurations.

6.1. Unweighted Model (CLOGIT)

We begin with the basic conditional logit model with all of the main effects (e.g., *Fee*, *Toilet*, *Trail*, *Picnic*, *NoCrowd*, *NoLitter*, *Birds*, *Stream*, and *Info*), and then systematically interact each main effect with respondent characteristics from the survey instrument. These characteristics are described in Table 5 under three categories: respondent/household characteristics, respondent attitudes, and enumerator responses related to the interview.[23] We also include the interaction terms between the

[23] Recall that all of the attribute variables are 0–1 indicator variables except for the *Fee* variable; *Fee* is entered linearly. We tried a Box–Cox transformation on *Fee* using a grid search in the model reported below. This results in an exponent of 0.948, which is not significantly different than the value of 1 (the linear specification) using a likelihood ratio test (likelihood ratio statistic of 0.2314; p-value = 0.63). An alternative specification of allowing each level of the *Fee* variable to have its own coefficient (normalizing 0 at zero) yields a likelihood ratio test statistic of 0.7642, which is distributed as a chi-square(df = 3) variable and has a p-value of .86.

Table 6
Interaction acronyms and definitions and summary statistics.

Variable	Description: Triggers if…	Mean
Fee30	Age ≤30	1.4163
FeeLowInc	Income <4	3.2619
FeeHH2	HHsize <3	0.8335
FeeTrip	Visited_AnyState == 1	3.1659
FeeCH	EthnicRecode == 2	1.0247
FeeIntShort	IntLength <25	0.7908
FeeIntLong	IntLength >70	0.8896
FeeTbVImp	Timber == 1	1.0268
FeeTbLImp	Timber == 3 | Timber == 4	1.4469
FeeWise	GovWise == 1	0.8837
FeeAtt23	Attempt==2 | Attempt==3	1.6518
ToiletUS	Strata3 == 2	0.1231
ToiletCH	EthnicRecode == 2	0.0666
ToiletFem	Gender == 2	0.1611
Toilet60	Age ≥60	0.0377
ToiletTrips4	TotalTrips_AllStates >3 & <366	0.0593
TrailRS	Strata3==3	0.1314
TrailIN	EthnicRecode3==3	0.0480
TrailFem	Gender==2	0.1578
TrailEng	SurveyLang==1	0.0435
TrailCity	Childplace==3	0.0671
TrailNoSel	Visited_AnyExclSlangor==1	0.1459
TrailNoWork	Job==9	0.1010
PicnicEng	SurveyLang==1	0.0407
PicnicCity	Childplace==3	0.0652
PicnicCollege	Edu==7 | Edu==8	0.0416
PicnicTrips4	TotalTrips_AllStates >3 & <366	0.0596
PicnicNoWork	Job==9	0.1040
PicnicAtt2	Attempt==2 | Attempt==3	0.1068
NoCrowdFem	Gender==2	0.3208
NoCrowd30	Age ≤30	0.1819
NoCrowdEnv	Envist==1	0.2888
NoCrowdOverS	TripOverseas==1	0.1342
NoCrowdKL	Strata3==1	0.1612
NoLitterUS	Strata3==2	0.2412
Variable	**Description: Triggers if…**	**Mean**
NoLitterFem	Gender==2	0.3204
NoLitter60	Age ≥60	0.0753
NoLitterHHL	HHsize >5 & HHsize <26	0.1910
NoLitterCH	EthnicRecode3==2	0.1273
NoLitterEng	SurveyLang==1	0.0808
NoLitterRural	Childplace==1	0.3965
NoLitterTbVImp	Timber==1	0.1289
NoLitterBus	Job==2 | Job==3	0.0744
NoLitterProtect	EconVsEnv==2	0.4930
NoLitterOverS	TripOverseas==1	0.1304
BirdsCH	EthnicRecode3==2	0.0665
BirdsIN	EthnicRecode3==3	0.0411
BirdsRS	Strata3==3	0.0000
BirdsCity	Childplace==3	0.0710
BirdsChild	Children >0 & Children <50	0.2132
BirdsProtect	EconVsEnv==2	0.2453
BirdsTrips4	TotalTrips_AllStates >3 & <366	0.0595
BirdsNoWork	Job==9	0.1018
StreamUS	Strata3==2	0.1197
StreamRS	Strata3==3	0.1291
StreamNoWork	Job==9	0.1020
InfoTown	Childplace==2	0.0653
InfoCity	Childplace==3	0.0707
InfoBus	Job==2 | Job==3	0.0379
InfoTrips4	TotalTrips_AllStates >3 & <366	0.0591
InfoAtt23	Attempt==2 | Attempt==3	0.1031
Two-way interactions	**Defined by**	**Mean**
ToiletPicnic	Toilet × picnic	0.1642
ToiletBirds	Toilet × birds	0.1657
ToiletInfo	Toilet × info	0.1672
TrailBirds	Trail × birds	0.1630
PicnicNoCrowd	Picnic × nocrowd	0.1683
BirdsStream	Birds × stream	0.1669

Table 7
Fully parameterized conditional logit model (CLOGIT).

PChoice	Coef.	Std. err.
Fee	−0.142***	0.0142
FeeTrip	0.035***	0.0103
FeeHH2	−0.026*	0.0136
Fee30	0.039***	0.0117
FeeCH	0.041***	0.0135
FeeLowInc	0.030***	0.0105
FeeIntShort	0.031**	0.0134
FeeIntLong	−0.045***	0.0130
FeeTVImp	0.020	0.0133
FeeTLImp	−0.015	0.0113
FeeWise	0.033**	0.0129
Toilet	0.929***	0.1497
ToiletUS	−0.285**	0.1246
ToiletCH	−0.739***	0.1523
ToiletFem	0.307**	0.1225
Toilet60	0.723***	0.2030
ToiletTrips4	0.302*	0.1637
Trail	0.122	0.1222
TrailFem	−0.262**	0.1233
TrailEng	0.471***	0.1720
TrailCity	−0.435***	0.1455
TrailNoWork	0.205	0.1353
TrailNoSel	0.301***	0.1129
Picnic	0.412***	0.1355
PicnicEng	−0.388**	0.1875
PicnicCity	0.240	0.1585
PicnicCollege	0.292	0.1839
PicnicNoWork	−0.197	0.1401
PicnicTrips4	−0.319*	0.1650
NoCrowd	0.077	0.1272
NoCrowdFem	0.257**	0.1243
NoCrowd30	−0.261*	0.1408
NoCrowdEnv	0.170	0.1161
NoCrowdOverS	−0.407***	0.1515
NoLitter	0.190	0.1684
NoLitterUS	−0.289**	0.1246
NoLitterFem	0.176	0.1194
NoLitter60	0.282	0.1939
NoLitterHHL	0.172	0.1248
NoLitterEng	−0.445**	0.1769
NoLitterRural	−0.190	0.1206
NoLitterBus	0.484**	0.1912
NoLitterTVImp	−0.242*	0.1485
NoLitterProt	0.242**	0.1325
NoLitterOverS	0.196	0.1493
Birds	0.482***	0.1733
BirdsIN	0.307*	0.1613
BirdsCity	−0.246*	0.1382
BirdsChild	0.181	0.1158
BirdsNoWork	0.184	0.1276
BirdsProtect	0.215*	0.1265
BirdsTrips4	−0.217	0.1510
Stream	0.504***	0.1125
StreamUS	0.218*	0.1237
StreamNoWork	−0.277**	0.1322
Info	0.292***	0.1058
InfoCity	0.381***	0.1441
InfoBus	0.382**	0.1808
InfoTrips4	−0.286*	0.1514
InfoAtt23	−0.187	0.1201
ToiletPicnic	0.245*	0.1283
ToiletBirds	−0.208*	0.1200
ToiletInfo	0.251**	0.1258
TrailBirds	−0.212*	0.1260
PicnicNoCrowd	−0.363***	0.1229
BirdsStream	−0.171	0.1258

Conditional (fixed-effects) logistic regression (N = 7566); LR chi2(66) = 954.94; Prob > chi2 = 0.0000; Log likelihood = −2293.2292; Pseudo R = 0.1723.
* Statistically significant at the 10% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 1% level.

main effects. Following custom, we retain all of the individual main effects in the final model irrespective of their significance levels. We will refer to this model as the CLOGIT model.

Interaction terms in this model were retained if they had an (absolute) z-statistic of 1.28, which corresponds to the 10% significance level for a one-sided hypothesis test.[24] A very large number of interaction terms were excluded due to their insignificant (and generally small in absolute-value terms) coefficients. The retained interaction terms are defined in Table 6, and estimation results are shown in Table 7. The final model includes 66 parameters, 9 for the main effects and 57 for the interactions. Interactions are grouped with the main effect variable that they modify. The only exception is that the two-way interactions between the main effects of the model appear at the end of the model specification.[25] The parameters for these interactions tend to suggest an intuitive pattern: interactions between people-friendly attributes such as *toilet* × *picnic* tend to have positive correlations, suggesting joint provision of these two attributes is super-additive, while interactions between people and wildlife-friendly attributes such as *birds* × *trail* tend to have a negative sign, indicating that joint provision is subadditive.

6.2. Weighted Model (WCLOGIT)

The corresponding results from a fully parameterized conditional logit model using the svy: complex survey weights, which we label as WCLOGIT, are provided as Table 8. We applied the same strategy as that adopted for the CLOGIT model in Table 7 of systematically dropping variables that do not meet an approximate 10% one-sided inclusion criterion. Dropping the weak predictors and adding some new interactions whose predictive ability is enhanced by the weighting, we now have 52 rather than 66 predictors. There are more interactions with strata and ethnicity, and there are sizeable interactions of the variable for respondents interviewed on the second or third attempt with *Fee* (*FEEAtt23*, −0.033; t = −2.04) and *Picnic* (*PicnicAtt23*, 0.355; t = 1.76). The *FeeAtt23* coefficient suggests that those interviewed in the second or third wave are willing to pay 80% of those interviewed in the first wave.[26] Overall, however, the WCLOGIT results are qualitatively quite similar to those for the CLOGIT model: almost all of the parameters have the same sign, and most are of similar magnitude, particularly after they are expressed in terms of WTP.

A comparison of the parameters on the *Fee* variable in Tables 7 and 8 suggests that the WTP estimates from the WCLOGIT model will be 93% of those from the CLOGIT model. However, a comparison of the parameter estimates on the *Toilet* main effects variable in Tables 7 and 8 suggests that the parameter estimate from the WCLOGIT model is larger (1.329 vs. 0.929) than the estimate from the CLOGIT model; consequently, marginal WTP estimates for *Toilet* for a respondent for whom all the interaction terms are zero is RM 10.22 in the WCLOGIT model and only RM 6.54 in the CLOGIT model. Other WTP calculations using data from the two models vary, sometimes with higher and sometimes with lower values.

The obvious difference between the models is that most of the z-statistics in the WCLOGIT model in Table 9 are smaller. Most of the variables are, however, still statistically significant according to our

Table 8
Fully parameterized conditional logit model with survey weights (WCLOGIT).

PChoice	Coef.	Linearized std. err.
Fee	−0.130***	0.0200
FeeTrip	0.038***	0.0144
FeeHH2	−0.033*	0.0183
Fee30	0.025	0.0157
FeeCH	0.074***	0.0192
FeeLowInc	0.048***	0.0177
FeeIntShort	0.038**	0.0186
FeeIntLong	−0.038*	0.0200
FeeTbLImp	−0.033**	0.0155
FeeAtt23	−0.033**	0.0162
Toilet	1.329***	0.1953
ToiletUS	−0.363**	0.1787
ToiletCH	−0.645***	0.1953
Toilet60	0.332	0.2371
Trail	0.272	0.1958
TrailRS	−0.207	0.1390
TrailIN	0.306	0.2008
TrailFem	−0.499***	0.1463
TrailCity	−0.244	0.1933
TrailNoWork	0.257	0.1654
TrailNoSel	0.281*	0.1576
Picnic	0.302**	0.1379
PicnicEng	−0.419**	0.1895
PicnicCity	0.311	0.2089
PicnicAtt23	0.355*	0.2018
NoCrowd	0.196	0.1489
NoCrowdKL	0.293	0.1928
NoCrowd30	−0.322**	0.1605
NoCrowdEnv	0.228	0.1481
NoCrowdOverS	−0.656***	0.1631
NoLitter	0.082	0.1897
NoLitterUS	−0.302**	0.1463
NoLitterCH	0.463**	0.1820
NoLitterEng	−0.706***	0.2093
NoLitterBus	0.586***	0.1995
NoLitterProt	0.355*	0.1941
Birds	0.314	0.2117
BirdsRS	−0.218	0.1590
BirdsCity	−0.459***	0.1767
BirdsChild	0.301**	0.1524
BirdsProtect	0.452***	0.1714
Stream	0.551***	0.0947
StreamRS	−0.290*	0.1714
Info	0.368***	0.1336
InfoCity	0.304*	0.1740
InfoBus	0.308*	0.1758
InfoTrips4	−0.449**	0.1858
InfoAtt23	−0.243	0.1685
ToiletBirds	−0.217	0.1796
ToiletInfo	0.221	0.1693
TrailBirds	−0.295	0.1858
PicnicNoCrowd	−0.269*	0.1437

Conditional (fixed-effects) logistic regression (N = 7566); F(52, 149) = 13.37; Prob > F = 0.0000.
* Statistically significant at the 10% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 1% level.

Table 9
Summary statistics for competing WTP estimators (RM)*.

Variable	Obs	Mean	Std. dev	Min	Max
Median7	256	18.40554	8.308438	0	37.6757
Mean7	256	34.97491	16.165500	−2.198581	77.9691
Mean7WN	256	22.66568	10.246200	0	46.2415
Mean7WNWT	256	22.92732	10.217320	0	47.4040
Median8	256	19.14509	8.598756	0	38.5091
Mean8	256	26.54511	11.477850	0	53.2146
Mean8WN	256	25.72704	11.399430	0	52.7128
Mean8WNWT	256	26.05836	11.196300	0	53.7499

[24] It should be clearly noted that reported significance levels are not strictly valid given the specification search used in developing this model (Leamer, 1983; Caudill and Holcombe, 1999).
[25] We do not consider higher-order interactions as these are not statistically identified in our design.
[26] The most noticeable issue raised by the first wave of the survey is that the fraction of the sample who are of Chinese ethnicity is substantially lower than official census estimates. The deficit of Chinese respondents is progressively reduced in the second and third wave of the survey.

inclusion criteria.[27] However, 13 of our parameter estimates (five of them interactions with *NoLitter*) now have z-statistics that have fallen below 1.0, which is the cutoff in an OLS regression model for when a variable improves or reduces several standard goodness of fit measures (thus penalizing the inclusion of variables which do not explain enough variance to compensate for their impact on a model's number of degrees of freedom).[28]

6.3. Calculating the Value of Different Park Configurations

With eight binary attributes there are 256 ($=2^8$) possible park configurations for which our model can produce valuation estimates. The calculation for the i^{th} respondent and the j^{th} park configuration is straightforward under the typical assumptions[29]:

$$\begin{aligned}\mathrm{WTP}_{ij} = \Big(&\textstyle\sum_k \alpha_k [\mathrm{ME}_{ijk}] \\ &+\textstyle\sum_k \beta_k \left[\text{Interactions of } \mathrm{ME}_{ijk} \text{ with characteristics of respondent i}\right] \\ &+\textstyle\sum_k \gamma_k \left[\text{Two way interactions between the } \mathrm{ME}_{ijk}\right)\Big. \\ &\Big/ (\Theta[\text{Coefficient on } \mathit{Fee}] + \psi[\text{Interactions with } \mathit{Fee}(=1)]),\end{aligned}$$

where α_k, β_k, γ_k Θ, and ψ are parameters to be estimated and k, an index of variables to be summed over, can differ by variable. ME_{ijk} represents the value of one of the $k = 9$ main effect variables assigned by the DCE to respondent i for park configuration j. The second line of this expression contains interactions between the ME_{ijk} and a set of variables representing respondent characteristics. The third line contains interactions between the different ME_{ijk}, where it is important to note that there are no quadratic terms because all of the ME_{ijk} are indicator variables. The fourth line contains the overall marginal utility of the money parameter in the form of the Θ coefficient on *Fee* plus a set of interactions between respondent characteristics and *Fee* that allow the marginal utility of income to be different for respondents with different observed characteristics. In thinking about the calculation of WTP for a particular park configuration, it may be useful to distinguish between interactions that shift the *Fee* parameter, which will show up in the denominator of the WTP calculation, and those that influence the relative attractiveness of a particular park configuration that influence the numerator of that calculation. In models with interactions such as those in Tables 7 and 8, there is a full range of interaction terms that enter the WTP calculation.

Given our distributional assumption, the simple conditional logit model produces a single mean (and median given the symmetry assumption) value of WTP for each possible park configuration, since respondent characteristics do not enter into the calculation. In the fully parameterized conditional logit models, an estimate of the conditional expectation of WTP is produced for each respondent and each park configuration. It is possible then to take the overall mean and median WTP for the park configuration, where these two estimates need not be the same.

We performed this exercise for each of the 256 park configurations, using estimation results from the WCLOGIT model. In doing so, a potential problem raised above in a footnote arises in our data. Allowing extensive interactions between respondent characteristics and the *Fee* variable creates a rich picture of price responsiveness, which we would ideally like to model. However, a problem emerges in doing this which is similar to what can happen in a mixed logit model: some fraction of the respondents for some park configurations are predicted to have a denominator for the WTP calculation that is close to zero. In our case, this tends to occur when there are several non-zero interaction terms involving the entrance fee that are added together. This creates overall WTP estimates for an attribute or a park configuration that are large in magnitude (either negative or positive) and are not reflective of the sample as a whole.

We take a common but somewhat ad hoc approach to dealing with this issue and "Winsorize" (Dixon and Yuen, 1974) the WTP estimates for each park configuration, with the percentile at each tail placed at 5% being substituted for individual values that are smaller or larger than the 5th or 95th percentile. The Winsorization approach is identical to a trimmed mean if the underlying distribution is symmetric, and it does a better job of maintaining the asymmetric nature of a distribution when symmetry does not hold. The main advantage in our case, though, of using the quite light 5% Winsorization is that it allows us to look at differences in various subsamples defined by variables such as geographic strata without having to worry whether we are excluding different fractions of the observations.

6.4. Examination of the Distribution of WTP for Different Park Configurations

There are a number of different WTP statistics that could be used to represent the public's value for a particular park configuration and to rank order different park configurations. For the latter purpose, it is worth noting that all of the commonly used summary statistics for WTP are highly correlated, with the smallest correlation between the different WTP measures being 0.94. This suggests that the choice of WTP statistic does not have substantial influence on the rank order of park configurations.[30]

We display graphs and tables only for median WTP and the Winsorized estimate based on the WCLOGIT model in Table 8. We prefer the WCLOGIT model to the CLOGIT model in Table 7 for two reasons. First, the WCLOGIT model is a bit more parsimonious than the CLOGIT model (52 parameters vs. 66), and hence it is probably somewhat less likely to overfit. Second, the Winsorization process has relatively less impact on the WCLOGIT estimates for each park than it does on the CLOGIT estimates. This can be seen in Table 9, which produces the summary statistics for the main competing estimators of WTP. Note that the medians produced from the estimates in Tables 7 and 8 are less than one RM apart and that applying the svy: weights to the Winsorized means also produces little change in the mean estimate of WTP averaged over all park configurations. The highest average estimate is produced by calculating mean WTP from the CLOGIT model, which we label *Mean7*, but it has some very extreme predictions, with the minimum going into the negative range and the maximum being over RM 30 higher than the maximum for any of the other estimators. Winsorizing, of course, eliminates this problem. The weighted Winsorized WCLOGIT estimate, *Mean8WNWT*, is a bit higher than the corresponding CLOGIT estimate, *Mean7WNWT*, but it is very similar to the unweighted and un-Winsorized WCLOGIT counterparts.

Fig. 1a and 1b display the distributions of the median and Winsorized mean WTP for each of the 256 park configurations using the Table 8 WCLOGIT model. The distribution of the Winsorized mean

[27] This observation is not uniformly true and appears to be violated when the interaction term involves a variable closely related to the weighting scheme. For instance, the parameter on *FeeCH* (the *Fee* interaction with Chinese ethnicity) has a z-statistic of 3.04 in the CLOGIT model and 3.85 in the WCLOGIT model. In a limited amount of experimentation with the WCLOGIT model, we came across one variable of interest that is close to zero in the CLOGIT model and marginally significant in the WCLOGIT model, and that is *FEEAtt23*, which is the interaction of *Fee* with having been interviewed on the second or third attempt. The WCLOGIT parameter estimate is negative, -0.033 ($z = -2.04$) suggesting that WTP of respondents interviewed in a later attempt is 87% of those interviewed in the first attempt. In contrast, inclusion of this variable in the CLOGIT model yields a point estimate of -0.0018 ($t = -0.16$), which suggests that WTP for these respondents is 99% of those interviewed in the first attempt.

[28] However, the adjustment for clustering is likely to be too severe and weighting schemes often result in smaller interaction parameters because they can reduce the amount of information contained in the original sample by down-weighting observations to obtain the requisite balance required by the weighting scheme.

[29] These assumptions are that the marginal value of income is acceptably proxied by the coefficient on the *Fee* variable and that there is no need to make corrections for random components.

[30] Online appendix Table 10o provides the correlation matrix between these different estimates of WTP.

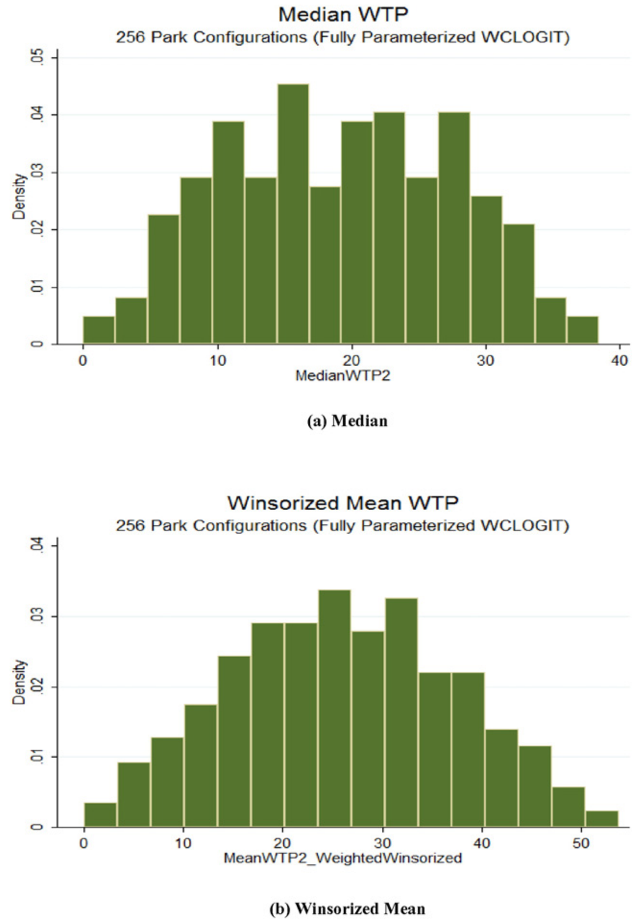

Fig. 1. Histograms of park WTP using WCLOGIT model (RM) (a) median (b) winsorized mean.

estimates is spread out more than the distribution of the median estimates. Given that we have WTP estimates for each park, it is possible to determine the ten most preferred parks. This ranking can be done based on any desired summary statistic such as median or mean WTP. It can be done for the sample as a whole, or it can be done for particular subsamples such as those defined by the three geographic strata or the three ethnic groups. The top ten ranked park configurations using the median estimate for each park based on the WCLOGIT model are provided below in Table 10. All of the most preferred parks have *Toilet*, *Birds*, *Stream*, and *Info* equal to one (i.e., these features are present at the park), but they differ with respect to the other attribute levels. Use of alternative summary statistics can alter the perception of the most desired park configurations, but, near the top, park configurations tend to shift up or down by a fairly small number of ranks. There are larger differences in rankings between different subsamples defined by geographic strata or ethnicity. These differences could be relevant in specific decisions on how to configure particular parks.

Table 10
Ten top ranked parks using estimated median WTP (RM)*.

Rank	Park Number	WTP	Attributes (toilet, trail, picnic, no crowds, no litter, birds, stream, information)
1	246	11.94	1, 0, 1, 0, 1, 1, 1, 1
2	254	11.66	1, 0, 1, 1, 1, 1, 1, 1
3	248	11.37	1, 1, 1, 0, 1, 1, 1, 1
4	230	11.14	1, 0, 1, 0, 0, 1, 1, 1
5	250	11.05	1, 0, 0, 1, 1, 1, 1, 1
6	256	10.95	1, 1, 1, 1, 1, 1, 1, 1
7	216	10.75	1, 1, 1, 0, 1, 0, 1, 1
8	238	10.62	1, 0, 1, 1, 0, 1, 1, 1
9	242	10.43	1, 0, 0, 0, 1, 1, 1, 1
10	182	10.39	1, 0, 1, 0, 1, 1, 0, 1

* Based on WCLOGIT.

7. Discussion and Concluding Remarks

The information gathered from our DCEs is incredibly rich and enabled us to estimate models that allowed a large degree of heterogeneity among household preferences. However, for all but two of the park attributes, the type of trails and the degree of crowding, there is effectively almost complete agreement on the most preferred levels of the attributes of a new park. Where heterogeneity comes into play is in the tradeoffs respondents are willing to make to obtain one of these preferred attribute levels relative to some other attribute level. The most important attribute level for most respondents is the presence of toilets and drinking water. With respect to other attributes, the basic conditional logit model suggests that respondents put roughly equal weight on several of them. Mixed logit models suggest considerable preference dispersion with respect to these attributes. Finally, our fully parameterized conditional logit models allow us to identify observable respondent characteristics that drive the preference heterogeneity across park attributes.

Indeed, in the fully parameterized conditional logit model, we observe differences across the three geographic strata (Kuala Lumpur, urban Selangor, and rural Selangor), the three main ethnic groupings (Bumiputera, Chinese, and Indian), household size and income, the presence of children, the nature of employment (with those not working often having different preferences), past recreation behavior, several indicators of environmental attitudes, and variables related to survey administration. In some cases, this heterogeneity manifests itself in terms of interactions with the *Fee* variable, and it shifts WTP for a park configuration up or down while leaving the relative ranking of park options intact. In other instances, these interactions modify the preference parameters for the main effects park configuration attribute variables and thus shift relative rankings of different configurations. For any particular park configuration, it is possible to look at differences in mean and median WTP by a number of variables of potential policy interest. This can provide a key input into the decision-making process when the cost of providing a park with a particular set of attribute levels is considered along with the particular location.

We devoted substantial effort to econometric modeling and weighting issues. Here a basic unweighted conditional logit model provides reliable insights into how respondents, on average, view tradeoffs among park attributes. Using the complex survey weights changes the parameter estimates a bit, yet most of the effect is to increase the standard errors. If one believes that the sort of clustering typically used in high quality surveys of this sort reduces the effective sample size as much as the pessimistic assumptions suggest, then the much smaller sample sizes often used in valuation studies in developing countries may be problematic.

We find that mixed logit models, with and without correlation between the attributes, perform well in capturing the underlying preference heterogeneity and providing a good fit to the data. It took considerable effort at a specification search to find a set of interaction terms for a conditional logit model that provided a better in-sample log-likelihood. Yet, mixed logit models and their results are problematic for two reasons. First, while one gets a sense of the magnitude of the underlying distribution of a particular preference parameter, it is unclear what is driving that preference heterogeneity. The fully parameterized conditional logit approach is better suited for this task, but it requires a reasonably rich dataset of potential covariates. Second, the mixed logit parameter estimates (and in turn various WTP estimates) are sometimes hard to interpret, numerically unstable, or provide implausible parameter estimates as one moves to: (a) models with a large number of parameters, (b) non-normal assumptions about the underlying parameter distributions, (c) allowing the *Fee* variable to have a random distribution rather than being fixed, and (d) simultaneously controlling for the possibility of heterogeneity in the scale of the error component.

While all of these issues with mixed logit models have been addressed in the literature (Train, 2009), the level of skill and programming expertise required to accurately estimate complex mixed logit models and related statistics may make it difficult for forest managers and park planners in developing countries to implement them, and even conditional logit models, routinely. Routine implementation of these models in developing countries will likely require collaboration with researchers at local universities and institutes or, if local expertise is lacking, international partners. Thanks to the rapid growth of environmental economics capacity in developing countries (see the June, 2014 special issue of *Environment and Development Economics*), the constraint on local expertise is becoming less binding.

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Appendix 1. Illustrative Park Configuration Show Card

Features at a new park	Plan A	Plan B
Drinking water and toilets	None	Several
Walking trails	Dirt/gravel	Paved
Picnic tables and grills	None	None
Level of crowdedness	Many people present	Few people present
Litter at the park	No noticeable litter	No noticeable litter
Likelihood of seeing wildlife or birds	Rarely see wildlife/birds	Always see some wildlife/birds
Access to a stream or waterfall	Easy access to stream or waterfall	No access to streams or waterfall
Visitor information	None	None
Entrance fee (RM)	15	10

Appendix 2. Supplementary Data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.ecolecon.2015.10.009.

References

Abildtrup, J., Garcia, S., Olsen, S.B., Stenger, A., 2013. Spatial preference heterogeneity in forest recreation. Ecol. Econ. 92, 67–77.
Balmford, A., Beresford, J., Green, J., Naidoo, R., Walpole, M., Manica, A., 2009. A global perspective on trends in nature-based tourism. PLoS Biol. 7 (6), e1000144. http://dx.doi.org/10.1371/journal.pbio.1000144.
Barkmann, J., Glenk, K., Keil, A., Leemhuis, C., Dietrich, N., Gerold, G., Marggraf, R., 2008. Confronting unfamiliarity with ecosystem functions: the case of an ecosystem service approach to environmental valuation with stated preference methods. Ecol. Econ. 65 (1), 48–62.
Bowker, J.M., Leeworthy, V.R., 1998. Accounting for ethnicity in recreation demand: a flexible count data approach. J. Leis. Res. 30 (1), 64–78.
Carr, D.S., Williams, D.R., 1993. Understanding the role of ethnicity in outdoor recreation experiences. J. Leis. Res. 25 (1), 22–38.
Caudill, S., Holcombe, R., 1999. Specification search and levels of significance. East. Econ. J. 25 (3), 289–300.
Chase, L., Lee, D., Schulze, W., Anderson, D., 1998. Ecotourism demand and differential pricing of national park access in Costa Rica. Land Econ. 74 (4), 466–482.
Christie, M., Hanley, N., Hynes, S., 2007. Valuing enhancements to forest recreation using choice experiment and contingent behaviour methods. J. For. Econ. 13 (2), 75–102.
Cochran, W.G., 1977. Sampling Techniques. 3rd edition. Wiley Press, New York.
DeShazo, J.R., Fermo, G., 2002. Designing choice sets for stated preference methods: the effects of complexity on choice consistency. J. Environ. Econ. Manag. 44 (1), 123–143.
DeShazo, J.R., Carson, R.T., Schwabe, K.A., Vincent, J.R., Ahmad, I., Chong, S.K., Chang, Y.T., 2015. Designing and implementing surveys to value tropical forests: a Malaysian application. J. Trop. For. Sci. 27, 92–114.
Dixon, W., Yuen, K., 1974. Trimming and winsorization: a review. Stat. Pap. 15 (2), 157–170.
Gelo, D., Koch, S., 2012. Does one size fit all? Heterogeneity in the valuation of community forestry programs. Ecol. Econ. 74, 85–94.
Hoyos, D., Mariel, P., Fernández-Macho, J., 2009. The influence of cultural identity on the WTP to protect natural resources: some empirical evidence. Ecol. Econ. 68 (8), 2372–2381.
Jacobsen, J.B., Thorsen, B.J., 2010. Preferences for site and environmental functions when selecting forthcoming national parks. Ecol. Econ. 69, 1532–1544.
Johnson, C.Y., Bowker, J.M., 1999. On-site wildland activity choices among African Americans and white Americans in the rural south: implications for management. J. Park. Recreat. Adm. 17 (1), 21–39.
Juutinen, A., Mitani, Y., Mantymaa, E., Yasushi, S., Siikamaki, P., Svento, R., 2011. Combining ecological and recreational aspects in national park management: a choice experiment application. Ecol. Econ. 70, 1231–1239.
Leamer, E., 1983. Specification Searches: Ad Hoc Inferences with Non-Experimental Data. Wiley Press, New York.
Lee, J.A., Soutar, G.N., Louviere, J., 2007. Measuring values using best-worst scaling: the LOV example. Psychol. Mark. 24 (12), 1043–1058.
Levy, P.S., Lemeshow, S.A., 2008. Sampling of Populations: Methods and Applications. 4th edition. Wiley Press, New York.
Li, C., Absher, J., Zinn, H., Graefe, A., Chick, G., 2010. A multi-ethnic comparison of perceptions of forest recreation service quality. J. Tour. Leis. Stud. 15 (3), 213–238.
Lindberg, K., Veisten, K., 2012. Local and non-local preferences for nature tourism facility development. Tour. Manag. Perspect. 4, 215–222.
Loomis, J., Walsh, R., 1997. Recreation Economic Decisions: Comparing Benefits and Costs. 2nd edition. Venture Publishing, State College, PA.
Loomis, J., Ellingson, L., Gonzalez-Caban, A., Seidl, A., 2006. The role of ethnicity and language in contingent valuation analysis. Am. J. Econ. Sociol. 65 (3), 559–586.
Mladenov, N., Gardiner, J., Flores, N., Mbaiwa, J., Mmopelwa, G., Strzepek, K., 2007. The value of wildlife-viewing tourism as an incentive for conservation of biodiversity in the Okavango Delta, Botswana. Dev. South. Afr. 24 (3), 409–423.
Mogas, J., Riera, P., Bennett, J., 2006. A comparison of contingent valuation and choice modelling with second-order interactions. J. For. Econ. 12, 5–30.
Naidoo, R., Adamowicz, W., 2005. Biodiversity and nature-based tourism at forest reserves in Uganda. Environ. Dev. Econ. 10, 159–178.
Onofri, L., Nunes, P., 2013. Beach 'lovers' and 'greens': a worldwide empirical analysis of coastal tourism. Ecol. Econ. 88, 49–56.
Othman, J., Bennett, J., 2004. Environmental values and resource management options: a choice modelling experience in Malaysia. Environ. Dev. Econ. 9, 803–824.
Revelt, D., Train, K., 1998. Mixed logit with repeated choices: households' choices of appliance efficiency level. Rev. Econ. Stat. 80 (4), 647–657.
Rolfe, J., Bennett, J., Louviere, J., 2000. Choice modelling and its potential application to tropical rainforest preservation. Ecol. Econ. 35, 289–302.
Samdin, Z., 2008. Willingness to pay in Taman Negara: a contingent valuation method. Int. J. Econ. Manag. 2 (1), 81–94.
Schwabe, K., Carson, R., Deshazo, J.R., Potts, M., Reese, A., Vincent, J.R., 2015. Creation of Malaysia's Royal Belum State Park: a case study of conservation in a developing country. J. Environ. Dev. 24, 54–81.
StataCorp, 2011a. Stata Survey Data Reference Manual: Release 12. StataCorp, College Station, Texas.
StataCorp, 2011b. Stata Release 12. StataCorp, College Station, Texas.
Teasley, J.R., Bergstrom, J., Cordell, K., 1994. Estimating revenue-capture potential associated with public area recreation. J. Agric. Resour. Econ. 19 (1), 89–101.
Train, K., 2009. Discrete Choice Methods with Simulation. 2nd edition. Cambridge University Press, New York.
Vincent, J.R., Carson, R.T., DeShazo, J.R., Schwabe, K.A., Ahmad, I., Chong, S.K., Chang, Y.T., Potts, M.D., 2014. Tropical countries may be willing to pay more to protect their forests. Proc. Natl. Acad. Sci. 111 (28), 10113–10118.
Winter, P., Jeong, W., Godbey, G., 2004. Outdoor recreation among Asian Americans: a case study of San Francisco bay area residents. J. Park. Recreat. Adm. 22 (3), 114–136.
Zander, K.K., Straton, A., 2010. An economic assessment of the value of tropical river ecosystem services: heterogeneous preferences among aboriginal and non-aboriginal Australians. Ecol. Econ. 69 (12), 2417–2426.