Exploring the Cultural Value of Kapa Haka – the Māori Performing Arts – using a Binomial Logit and Other Travel Cost Models

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Abstract

We apply travel cost models to value a particular aspect of Māori culture, specifically, participation at the 2017 Te Matatini national kapa haka (Māori performing arts) festival. We compare the results of naive, and zonal, single site unrestricted count regression models of group visitor demand to attend the festival with the results of a novel restricted binomial logit demand model that is better tailored to our data. While the former models allow visitors to make any number of festival visits, the novel model reflects visitor groups' binary choice of whether to attend the festival or not. We show that estimated willingness to pay (WTP) for festival access is relatively invariant to specification of the unrestricted models, but is an order of magnitude lower for the restricted model. For the latter, WTP is estimated to be c. NZ$39.67 to NZ$51.56 per visitor group. Estimating other kapa haka use values (including any commercial value), and non-use values like its option, bequest and existence values, is left to future research.

JEL Classifications: A13, C25, C54, J15, Z13.

Keywords: Māori, Kapa Haka, Cultural Values, Non-Market Valuation, Travel Cost Models, Willingness to Pay.

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1 Introduction

Cultural values can take on great significance when sites of cultural significance are lost to natural or man-made harms.[1] While the loss of cultural practices (language, music, etc) can be less sudden and conspicuous, it too can also be keenly felt, by both the communities defined by those practices, and the wider societies which they enrich. Conversely, cultural practices are more likely to be properly considered for policy purposes (e.g. applications for public funding) if their value, and not just their costs, are available to decision-makers.

A pressing issue in all such cases is establishing how cultural values should be defined and measured. This might be done *ex post*, such as when assessing damages for cultural harms. Alternatively, it can be done prospectively, to better understand the worth of preserving or enhancing cultural values. However, many aspects of culture share features with public goods, in that they are both non-rivalrous and non-exhaustible.[2] As a consequence, most aspects of culture are not themselves traded in markets with observable prices, so valuing them requires use of non-market valuation (NMV) techniques.[3]

This study explores the value of kapa haka, the group-based performing arts of Māori, the indigenous people of New Zealand (Aotearoa), using NMV. Kapa haka combines the celebration of traditional and contemporary Māori culture, the practice and promotion of te reo Māori (the Māori language), and singing and dancing involving significant coordination and exertion. It also involves working with groups of people (across ages, genders and walks of life) that have shared values and other connections, towards a common goal, and with peer encouragement and monitoring. Its adherents report that involvement with kapa haka – whether as performer or spectator – is associated with improved mental and physical health, educational achievement, cultural vitality, and social cohesion (among other benefits).[4]

To explore aspects of the cultural value of kapa haka, this study applies both existing and novel approaches for implementing travel cost models (TCMs). TCMs are a revealed preference NMV technique commonly applied when estimating recreational demand for natural sites such as parks, lakes or

[1] Notable contemporary examples include the destruction of antiquities such as the Buddhas of Bamiyan in the Bamyan Valley (central Afghanistan), Palmyra in Homs (Syria), and 46,000 year old Aboriginal rock drawings in Western Pilbara (Australia).

[2] Indeed, one could say that some aspects of culture are the opposite of non-exhaustible – i.e. language, dance, music and other aspects of culture can be enhanced, rather than diminished, when practiced by a greater number of people.

[3] Comprehensive overviews of these techniques are available from multiple references, such as Haab and McConnell (2002), Freeman et al. (2014), and Champ et al. (2017).

[4] For an overview, see Pihama et al. (2014).

rivers. They estimate demand for visits to such sites by exploiting variation in the number of site visits, as well variation in the transport and travel time costs incurred by actual site visitors.[5] With demand estimated, it is then possible to estimate welfare metrics such as the willingness to pay (WTP, or consumer surplus) associated with access to the relevant site, representing the economic value captured by users of the site.

More specifically, this study uses survey data drawn from a random sample of visitors to the biennial Te Matatini national kapa haka festival held at Hastings, in the Hawke's Bay region of New Zealand, in February 2017. That data is combined with estimates of travel distances and travel times using information on survey respondents' place of residence, as well as sub-regional administrative demographics data. The combined dataset, comprising data for each of 100 geographical sub-regions, is then used to estimate visitor group demand for the Te Matatini festival using a zonal, single-site TCM based on visit data, exploiting variation in the number of visitors per sub-region, and in sub-regional transport and travel time costs. The resulting model for Te Matatini demand is then used to estimate visitor group WTP for access to the festival. This captures one aspect of the value of "using" kapa haka – namely the value of either performing kapa haka, or spectating, at the biennial national kapa haka festival.

A novel approach for specifying TCMs is presented, since data limitations require estimation of demand for a single visit to a single festival. This approach and its results are contrasted with those of conventional techniques for estimating zonal, single-site TCMs, which instead presume that visitors can make multiple visits to any given site in a given period.

Multiple NMV studies have been undertaken in New Zealand,[6] and they find use for policy purposes via metrics such as the value of statistical life, value of travel time, etc.[7] A number of New Zealand NMV studies include assessments of Māori cultural values attaching to natural resources.[8] However, to the author's knowledge, this is the first study to apply NMV techniques to explicitly quantify the value of an aspect of Māori culture itself.

This study therefore complements other existing studies of Māori cultural values. Those studies are either qualitative,[9] or quantitative but do not apply

[5] For example, see Haab and McConnell (2002), Freeman et al. (2014) or Champ et al. (2017) for detailed descriptions.

[6] See Yao and Kaval (2011) for a general survey, and Marsh and Mkwara (2013) for a survey of studies relating to freshwater values.

[7] For applications of such metrics in transport, see New Zealand Transport Agency (2018).

[8] For example, see Kerr and Sharp (2003), or Miller et al. (2015).

[9] For example, Pihama et al. (2014).

frameworks used for economic valuation.[10] Alternatively, they measure Māori cultural values in relation to specific natural resources.[11] This study also provides a benchmark against which to assess rules of thumb sometimes used for policy purposes to estimate consumer benefits from events like cultural festivals.[12]

We find that a key parameter required for estimating WTP for access to cultural festivals – the sensitivity of sub-regional demand for Te Matatini visits to changes in combined transport and travel time costs – is relatively invariant to model specification and solution technique when using either simple or more refined existing zonal, single-site TCMs. However, it changes materially when estimated using our novel TCM approach that is tailored to our data, and can be sensitive to the choice of solution technique when applying that approach.

More specifically, using a standard zonal, single-site TCM, we estimate that the WTP of an "average group" of visitors for access to the 2017 Te Matatini festival is almost NZ$29,000 in 2017.[13] However, applying our novel TCM (which is better tailored to our data), we find that these figures are orders of magnitude lower, at NZ$39.67 to NZ$51.56 per group on average, depending on how travel time costs are estimated. We also find that parameter estimates for our novel TCM are sensitive to the choice of how that model is implemented.

Our contribution is threefold. First, we apply NMV techniques to explicitly value an aspect of Māori culture itself. Second, in doing so, we develop a novel version of the zonal, single-site TCM reflecting limitations in our data. Finally, we show that the choice of NMV technique, or how it is implemented, can materially affect estimates of WTP for access to cultural events.

The rest of this paper is structured as follows. Section 2 sets out further details of the NMV framework applied in this study, and possible techniques for applying that framework to kapa haka. Section 3 sets out our empirical methodology, while Section 4 describes our data and assumptions. Section 5 presents our results, while Section 6 concludes, including with suggestions for future research.

[10] For example, Houkamau and Sibley (2019).

[11] Examples of comparable quantitative studies measuring Aboriginal cultural values associated with natural sites in Australia, but not of Aboriginal culture itself, include Rolfe and Windle (2003) and Zander et al. (2010).

[12] For example, Ministry of Business, Employment and Innovation (2013).

[13] When the Hastings Te Matatini festival was held in February 2017, NZ$1 = US$0.72.

2 Non-Market Valuation Framework and Techniques

2.1 Total Economic Value Framework

As a discipline, economics has long recognised that social values comprise more than just market values. Figure 1 illustrates how total economic value (TEV) is typically apportioned among different types of use and non-use values, taking kapa haka as the relevant "cultural good" to be valued.[14] As illustrated, the value of being able to access biennial Te Matatini national kapa haka festivals captures just one aspect of "in situ" kapa haka value. In turn, "in situ" value captures just one aspect of kapa haka's TEV. In estimating just this one aspect of use value, this study says nothing about the other possible kapa haka values illustrated in the figure.

2.2 Techniques for Non-Market Valuation

In the area of environmental economics, an array of NMV techniques has been developed, following the pioneering development of travel cost models (TCMs) in the 1940s.[15] They have grown to encompass further techniques such as contingent valuation, stated choice experiments based on random utility models, and hedonic pricing, to name just some of the main approaches.[16]

Insights from environmental economics, and the NMV techniques often used to value aspects of natural resources, have also found application in the growing field of cultural economics.[17] While sharing many of the issues central to non-market valuation in environmental economics, cultural economics emphasises additional issues. These include whether it is appropriate to ascribe individual-level values to culture instead of collective values, and hence whether techniques other than NMV methods might be more appropriate.[18]

[14]This figure adapts Figure 1 of Sharp and Kerr (2005), which relates to freshwater values rather than to the values associated with a specific cultural practice like kapa haka.

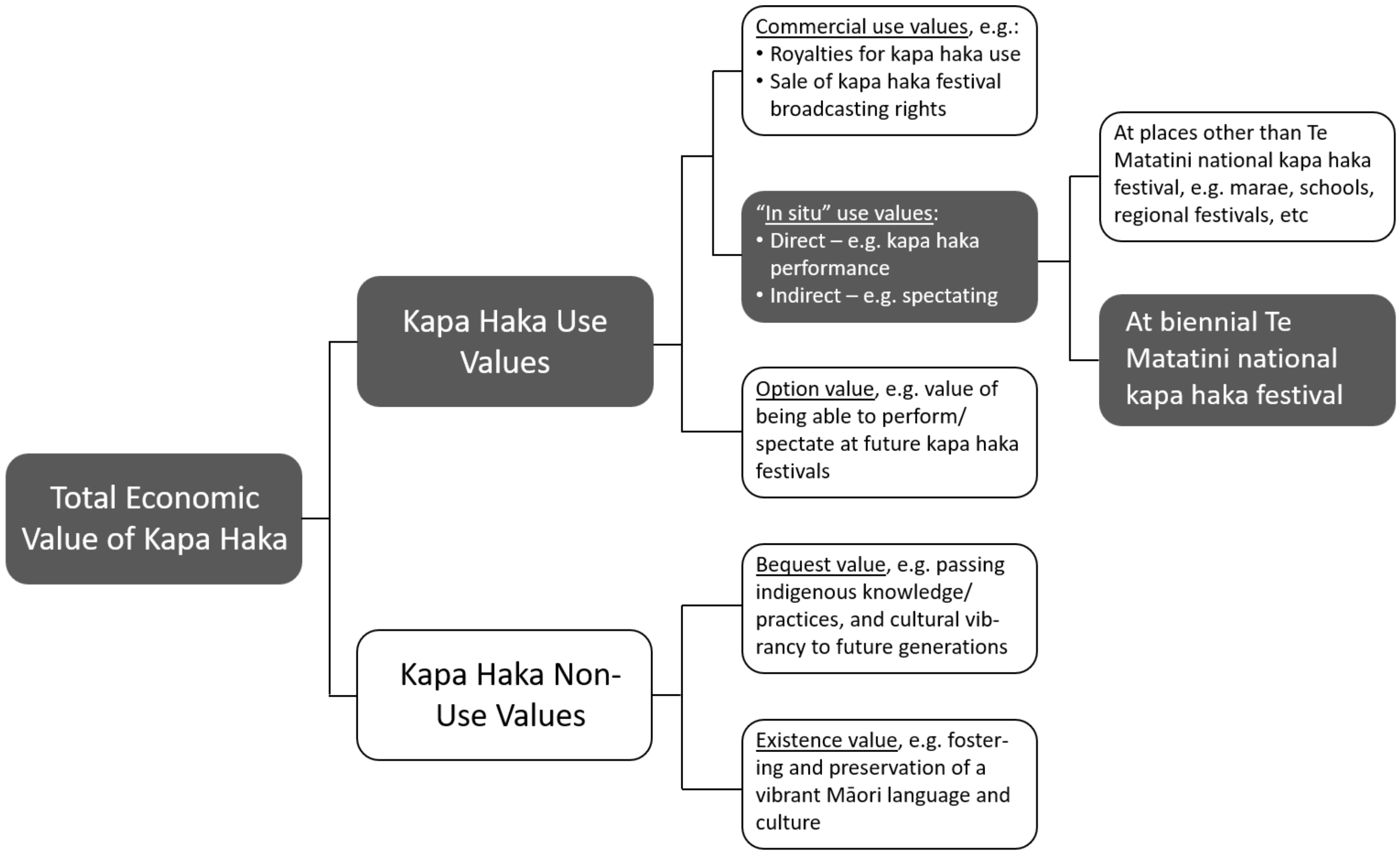
[15]Chapter 9 of Freeman et al. (2014) and chapter 6 of Champ et al. (2017) set out the historical development of TCMs, which date back to an unpublished 1947 letter from Harold Hotelling to the US Department of the Interior.

[16]See, for example, Haab and McConnell (2002), Freeman et al. (2014), or Champ et al. (2017), for details of each approach. Lupi et al. (2020) provide a guide as to best practice for implementing NMV studies.

[17]For overviews of the field, see Allan et al. (2013), Klamer (2013), Snowball (2011) or Throsby (2011). Snowball (2008, 2013) and Allan et al. (2013) detail the use of NMV techniques for measuring cultural values.

[18]Overviews are provided in Klamer (2013), and Snowball (2008, 2011).

Figure 1: Total Economic Value Framework Applied to Kapa Haka



However, within the discipline there seems to be agreement that valuation approaches commonly used for policy purposes – such as economic impact analyses based on the contribution of culture to GDP – are unduly limited in scope, and have questionable foundations.[19]

Additional cautions are sometimes raised when estimating NMVs for cultural values, and also more generally. Awatere (2005) questions whether they are suitable for valuing indigenous knowledge, though not specifically for valuing Māori culture. Finally, Bockstael et al. (2000) emphasise that NMVs do not value the object in question (e.g. an ecosystem) *per se*. Rather, they value changes in the state of that object – e.g. from an impaired to an improved state. These cautions aside, it is standard to apply NMV techniques to value *access* to a specific site or event, and NMV techniques represent the best available approaches for estimating cultural values.

Hence this study applies TCMs to value access to Te Matatini festivals, accepting that this measures just one aspect of the value of kapa haka, and that future research is warranted to provide both more comprehensive and/or appropriate estimates of kapa haka value.

3 Methodology for Estimating Visitor Group Demand

3.1 Zonal, Single-Site Travel Cost Model using Aggregated Data

Due to both the characteristics of Te Matatini, and limitations in our data (see Section 4), this study implements the simplest TCM variant. Specifically, a zonal, single-site TCM is implemented using aggregated data.

A single-site model was chosen because the biennial national kapa haka festival lacks obvious substitute events that visitors might have chosen to attend instead of Te Matatini. While kapa haka is performed and watched at various regional events, and also at traditional Māori communal meeting places (marae), schools, etc, the biennial Te Matatini festival is unrivalled in terms of its scale, profile and attendance.[20] It is also separated temporally

[19] Snowball (2008) provides an assessment. Bevin (2017) illustrates the application of economic impact analysis to Te Matatini festivals. Ministry of Business, Innovation and Employment (2013) outlines how it expects such analyses to be applied in New Zealand for policy purposes – e.g. for prioritising public funding for events like Te Matatini.

[20] According to Angus & Associates (2017), 19,670 adults attended the 2017 Hastings festival. By contrast, data supplied by Te Matatini indicates that 13 regional kapa haka events in 2018 drew audiences averaging just under 4,000 each.

from other kapa haka festivals, being staggered to not coincide with years in which regional festivals are held. Likewise, it is also scheduled so as to avoid clashes with other major events (e.g. national sporting events), in part to also ensure availability of a suitable venue.[21]

This serves to highlight how cultural events like Te Matatini – if not other cultural goods – can be distinguished from visits to recreational sites such as parks and lakes. While recreational sites are essentially fixed, and hence substitute sites are largely exogenous, cultural events like Te Matatini can be staged so as to avoid having close substitutes. This alone provides justification for not including information on substitute sites in the TCM specification, which commonly at least include travel cost details for substitute sites.[22]

Another reason for using a zonal, single-site model was because of limitations in our data. Survey data provides information on a sample of groups that visited the 2017 Te Matatini festival in Hastings, including the number of times they have attended Te Matatini festivals in the past, as well as details of where they reside. While the latter provides information useful for estimating individual groups' transport and travel time costs, the other survey data is insufficient to generate variation in the number of visits per Te Matatini group.

As a consequence, we combine information on the number of groups visiting the 2017 Te Matatini festival from each of 100 sub-regions to estimate the number of visiting groups per sub-region, similar to the approach in Hellerstein (1991). Variation in this number of visiting groups, combined with transport and travel time costs that vary by sub-region, provides the basis for estimating a group's demand for attending Te Matatini.

Groups of visitors are treated as being the relevant decision-making unit, rather than individuals. In part this is to reflect the importance of extended family (whānau) in Māori culture. It is also to reflect the fact that visitors to Te Matatini often travel in groups, which is relevant to the choice of transport mode when estimating transport and travel time costs (see Section 4 for further details).

[21] Personal communication, Linda Waimarie Nikora of Ngā Pae o te Māramatanga.

[22] It might be suggested that national marching competitions, or national marching band or pipe band competitions, are similar enough to kapa haka to represent viable substitutes. However, they too can endogenously be separated temporally from Te Matatini festivals, and have distinct cultural attributes that do not overlap with the Māori cultural attributes of Te Matatini. Hence these too are treated as not being sufficiently substitutable as to warrant inclusion in our demand models.

3.2 Naive Calibration Model

In the first instance, "naive" count regression models are estimated. These relate the number of visitor groups per sub-region to the 2017 Te Matatini festival with estimates of sub-regional transport and travel time costs and other explanatory variables. They are naive in the sense that they pay no explicit regard to the underlying data generating process – i.e. *a priori*, it is unclear whether they estimate the demand of individual groups, or of individual sub-regions.

The purpose of these models is to provide starting values of model parameters to be used when implementing other models. Such starting values are necessary because those models are solved numerically, and hence starting values are important for achieving convergence when estimating model parameters. These models are thus also described as being calibration models.

Count regression models are used because standard regression techniques fail to reflect the non-negative and integer nature of the dependent variable (here, number of visitor groups per sub-region attending Te Matatini).[23] In their simplest form, a Poisson model is postulated:

$$P\left(Y_j = n_j; n_j = 0,\, 1,\, 2, \ldots\right) = \frac{e^{-\lambda}\lambda^{n_j}}{n_j!} \tag{1}$$

where Y_j is the group demand for Te Matatini visits in sub-region j. Mean demand (and demand variance), λ, is modelled as being a function of explanatory variables x_j and coefficients (to be estimated) β. Since $\lambda > 0$, it is commonly modelled as $\lambda = exp\left(x_j\beta\right)$. The model's coefficients are estimated using maximum likelihood estimation (MLE).[24]

A common feature of recreation demand is that that it involves "over-dispersion" – e.g. relatively high frequencies of either no visits ("excess zeros") or very many visits ("avidity"). As such, the Poisson model's assumption that mean demand and demand variance are both equal to λ is commonly violated. A usual response is to fit more general count regression models, such as the Negative Binomial model – or Quasi-Poisson models – each of which better accommodates over-dispersion. While excess zeros and avidity are not anticipated to be particular features of our data, given our zonal approach, we estimate Quasi-Poisson and Negative Binomial models to compare with a standard Poisson model. We find this to be justified because over-dispersion remains a feature of our data.

[23]For practical introductions to count regression models, see Zeileis et al. (2008), or Beaujean and Grant (2016).

[24]See Greene (2003) for a description of MLE.

Hurdle models are also commonly applied when estimating count regression models.[25] This is to address either excess zeros, or an absence of zeros in the data due to endogenous selection (i.e. the only observations sampled are for those making visits). The problem of excess zeros is addressed by using mixture models to represent both the chance of zero counts arising due to decision-makers choosing not to visit a given site or event, and that of the decision-maker not being a visitor in the first place.

While the latter issue could be said to be a feature of decision-makers in relation to attending Te Matatini, we address this explicitly via the novel Binomial Logit model described below. Conversely, endogenous selection bias arises when avid users of a site or event are over-sampled by virtue of their more frequent use of the site or event. This is not a particular feature of our data, since the 2017 Te Matatini survey data simply records whether a group visited that particular festival or not. Hence, we have not estimated hurdle models for our particular demand context.

3.3 Reference Model

While the naive calibration model described above pays no explicit regard to the nature of the underlying data generation process, conventional zonal TCMs at least recognise that aggregating visitors by travel zone (e.g. in our case, sub-region) requires use of a count regression model that accounts for aggregation.

As described in Haab and McConnell (2002, pp 181-182), the Poisson model proves convenient due to its "adding up" property. Specifically, if z_j is the demand of a representative decision-maker (i.e. group, or individual) in zone j with mean demand λ_j, where N_j is the number of potential visitors (i.e. potential groups or individuals) in that zone, then aggregate demand in zone j is given by $Y_j \equiv N_j z_j$. If representative demand $P\left(z_j = n\right)$ follows a Poisson distribution, then by the Poisson distribution's adding up property aggregate demand can be modelled as:

$$P\left(Y_j = n_j; n_j = 0,\, 1,\, 2, \ldots\right) = \frac{e^{-N_j \lambda_j}\left(N_j \lambda_j\right)^{n_j}}{n_j!} \tag{2}$$

Substituting $\lambda_j = exp\left(x_j \beta\right)$, taking natural logs, and summing over observations from all J zones (i.e. sub-regions) provides the log-likelihood function

[25] See Zeileis et al. (2008) for details.

that can then be used to estimate β using MLE:[26]

$$lnL\left(\beta \mid X,Y\right)=\sum_{j=1}^{J}\left(-N_{j}exp\left(x_{j}\beta\right)+n_{j}\left[ln\left(N_{j}\right)+x_{j}\beta\right]-ln\left(n_{j}!\right)\right) \tag{3}$$

where X is the full matrix of explanatory variables across zones, and Y is the vector of visit counts across all zones. We take this to be a reference model, against which to compare the results of the novel Binomial Logit model described next.

3.4 Novel Binomial Logit Model

While the naive calibration model described above pays no explicit regard to the data generation process, the Poisson zonal reference model just described does not reflect the data generation process specific to our Te Matatini data. In particular, the reference model – like the naive calibration model – is "unrestricted" in the sense that it allows each decision-maker to make any number of visits to a particular site or event. However, since we are estimating group visitor demand for a given Te Matatini festival, which they either attend or not, a more suitable model would account for this underlying binary choice.

We therefore posit a "restricted", Binomial Logit, model to reflect any given group's decision whether or not to visit the 2017 Te Matatini festival. Formally, suppose the probability of a representative group t in sub-region (i.e. zone) j visiting the festival is:

$$P\left(y_{t,j}=1 \mid x_{t,j}\right)=\frac{exp\left(x_{t,j}\beta\right)}{1+exp\left(x_{t,j}\beta\right)} \tag{4}$$

where $y_{t,j}=1$ means the given group with explanatory variables $x_{t,j}$ (e.g. transport cost, travel time and demographic) visits Te Matatini. The probability of that representative group not attending the festival is thus:

$$P\left(y_{t,j}=0 \mid x_{t,j}\right)=1-\frac{exp\left(x_{t,j}\beta\right)}{1+exp\left(x_{t,j}\beta\right)}=\frac{1}{1+exp\left(x_{t,j}\beta\right)} \tag{5}$$

Assuming we have only sub-regional explanatory data for each such representative group in sub-region j (i.e. that $x_{t,j}\equiv x_{j}$ for all groups t in sub-region j), then the likelihood in a given sample of observing n_j visiting

[26] Haab and McConnell (2002, p. 182) omit the minus sign in the exponential of (2), with a corresponding omission of the initial minus sign shown in (3). Hellerstein (1991, p. 862) uses the form of aggregate demand as shown in (2), which leads to (3).

groups from that sub-region and therefore $N_j - n_j$ non-visiting groups, can be written as:

$$\begin{aligned} P\left(Y_j = n_j\right) &\equiv P\left(y_{1,j} = 1, \ldots, y_{n_j,j} = 1; y_{n_{j+1},j} = 0, \ldots, y_{N_j,j} = 0\right) \\ &= P\left(y_{t,j} = 1 \mid x_j\right)^{n_j} \left(1 - P\left(y_{t,j} = 1 \mid x_j\right)\right)^{N_j - n_j} \\ &= \left(\frac{exp\left(x_j\beta\right)}{1 + exp\left(x_j\beta\right)}\right)^{n_j} \left(\frac{1}{1 + exp\left(x_j\beta\right)}\right)^{N_j - n_j} \end{aligned} \tag{6}$$

Taking natural logs, summing over observations for all J sub-regions, and simplifying yields the log-likelihood function that can be used to estimate β using MLE:

$$lnL\left(\beta \mid X, Y\right) = \sum_{j=1}^{J} \left(n_j\left(x_j\beta\right) - N_j ln\left(1 + exp\left(x_j\beta\right)\right)\right) \tag{7}$$

3.5 Implementation

All of the above models were estimated in `R`. The Quasi-Poisson and Negative Binomial variants of naive calibration model (1) were estimated using predefined routines in `R`'s `glm` package.[27] Conversely, the reference model (2) and Binomial Logit model (6) were estimated using user-defined routines implemented with the `maxLik` package.[28]

Since MLE uses numerical search algorithms to estimate the value of β that maximises the relevant log-likelihood functions, it was necessary to specify both starting parameter values and search algorithms for models (2) and (6). As stated above, parameter estimates from the Quasi-Poisson version of the calibration model were used as the required starting values for those other models. In terms of search algorithms, `maxLik` supports multiple approaches. We used a variety, including Newton-Raphson (`NR`), Nelder-Mead (`NM`), simulated annealing (`SANN`) and Berndt-Hall-Hall-Hausman (`BHHH`).[29]

While the `NM` and `SANN` methods do not rely on information regarding log-likelihood gradients, for more complex models it is necessary to supply them (e.g. for the `NR` method), and it is essential to do so for the `BHHH` method. For the reference model (2), using x_{jk} to denote the k^{th} element of explanatory data row vector x_j, the gradient writes as:

$$\frac{\partial lnL\left(\beta \mid X, Y\right)}{\partial \beta_k} = \sum_{j=1}^{J} \left(n_j x_{jk} - N_j x_{jk} exp\left(x_j\beta\right)\right) \tag{8}$$

[27] See Zeileis et al. (2008) for details.
[28] See Henningsen and Toomet (2011) for details.
[29] Henningsen and Toomet (2011) provide further details.

Conversely, for the Binomial Logit model (6), the required log-likelihood gradient writes as:

$$\frac{\partial lnL\left(\beta \mid X, Y\right)}{\partial \beta_k} = \sum_{j=1}^{J} \left(n_j x_{jk} - \frac{N_j x_{jk} exp\left(x_j \beta\right)}{1 + exp\left(x_j \beta\right)} \right) \tag{9}$$

4 Data and Assumptions

4.1 Visitor Groups

The main data source enabling this study to be undertaken is a proprietary survey dataset provided by Te Matatini Society Incorporated. This dataset included random surveys of visitor groups to Te Matatini festivals in 2017 (Hastings) and 2019 (Wellington), with potential respondents identified on-site, but surveys conducted post-event in the weeks immediately following the festival.[30] As mentioned above, we model visitor groups as the relevant decision-making unit, not individual visitors.

While the 2017 survey provides us with details of which out of 100 sub-regions in which each respondent resided, it omits data on the size of each respondent's group. Hence data from the 2019 survey were used to estimate an average group size of c. 10 adults for the 2017 festival, since that survey included data on respondents' group sizes (but not their sub-regions of residence). Data on the 19,670 total number of adults attending the 2017 festival was obtained from Angus & Associates (2017), which was combined with estimated 10 adults per group to estimate the 1,967 total number of "average" groups attending that festival.[31]

As stated earlier, our dependent variable for our demand models is the number of average-sized groups from each of 100 possible sub-regions visiting the 2017 festival. Since the surveyed number of groups is less than the estimated total number of groups, positive counts for any given sub-region are re-scaled (and rounded to the nearest whole number) so that their total number matches the estimated 1,967 total number of average-sized visitor groups.[32] Where the survey reports no visitors from any given sub-region – which is the case for 29 of the 100 possible sub-regions specified in the survey – a zero visitor group count is assumed to apply in relation to all

[30]The 2017 survey, which provided our key data, comprised 903 completed responses, with a response rate of 49% (Angus & Associates (2017)).

[31]Hellerstein (1991) similarly uses average group size when implementing his zonal TCM using aggregated data.

[32]The aggregated sub-regional visitor counts differ slightly from 1,967 due to rounding each sub-regional count to whole numbers.

visitor groups (not just those surveyed). Respondents were excluded from our sample if they stated that visiting Te Matatini was not their main reason for visiting, or that they would have visited the region in any case. Respondents from outside New Zealand were also excluded.[33] After these exclusions, we were left with survey responses for 829 groups that attended the 2017 festival.

In the case of the Hastings sub-region, which hosted the 2017 festival, it is estimated that 228 average-sized groups of 10 adults each visited the festival. This is the single largest visitor group count of any sub-region, and created computational issues when implementing the user-defined models.[34] Accordingly, we capped the number of visitor groups from Hastings to be 170, for which all models could be estimated. To test the importance of this assumption, the Quasi-Poisson calibration model, which could be implemented with the actual Hastings group visitor count, was estimated using both the capped or uncapped visitor count. This indicated that it made less than a 4% difference on the estimated total travel cost coefficient in the demand model, which is key for estimating WTP for festival access. Hence, while undesirable, this assumption is likely to have a relatively modest impact on our results.

While the survey data distinguishes different types of visitor involvement (performing, spectating, etc), we do not distinguish between performers and spectators. In principle the value to performers from visiting Te Matatini festivals relates more to them enjoying a negative compensating wage differential – i.e. receiving benefits from performing over and above the nil wage they are paid for doing so.[35] This is to be contrasted with the consumer surplus derived by spectators visiting the festival. However, treating performers as being like spectators most likely mis-states their true value of attending Te Matatini festivals, since no account is made of the many hours that performers must spend preparing for the festival, and hence of the associated transport and travel time (and materials) costs they incur to perform.

Finally, when estimating the total potential number of visitor groups from any given sub-region (i.e. N_j), we do so using the estimated total Māori adults in that sub-region divided by our assumed average group size of 10 adults. We justify focusing just on the Māori adult population in each sub-region for this calculation, rather than the total adult population by sub-region, on the basis that 87% of 2017 survey respondents identified as Māori

[33] Angus & Associates (2017) report that non-resident visitors made up only 7% of respondents.

[34] For example, in Poisson-based models the log-likelihood requires calculation of $n_j!$, which is unmanageably large for $n_j = 228$.

[35] See Allan et al. (2013) for a discussion of compensating wage differentials in the context of cultural valuation.

(Angus & Associates (2017)).

4.2 Transport and Travel Time Costs

Overseas visitor groups – who in all probability would have flown to New Zealand and then driven to the festival – have been excluded from our sample. However, it remains possible that some domestic visitor groups would have also flown and/or driven to the festival.

The available survey dataset does not include data on respondents' travel modes, nor on the number of vehicles they may have used for their group. We assume that all domestic visitor groups travelled by motor vehicle. Where they travelled inter-island – i.e. to get from the South Island to the North Island for the festival in Hastings – it is assumed they took the drive-on drive-off Cook Strait ferry as part of an otherwise road-based voyage.

Google Maps data was used to estimate travel times and distances for each sub-region, which was then used to estimate transport and travel time costs by sub-region. Automobile Association reports were used to estimate per km vehicle running costs, which were applied to estimated travel distances, and added to inter-island ferry costs where appropriate) to arrive at estimated transport costs. As recommended by Lupi et al. (2020), estimated per km transport costs were adjusted to exclude costs not related to usage (i.e. registration, insurance and warrant of fitness costs). This resulted in an assumed per km transport cost of NZ$0.65/km, in 2017 dollars.

Per-km costs for medium-sized vehicles were adopted, since they also apply to minivans, meaning those costs apply for vehicles that can accommodate up to 12-15 passengers. In cases where the assumed average visitor group size relates to groups requiring larger vehicles, this assumption might serve to overstate transport costs, since large travelling groups could make use of coaches, for which the average transport cost per person is likely to be smaller.

For travel time costs, estimated travel times (including inter-island ferry times where appropriate) were multiplied by one third of average hourly wages, and scaled by the assumed 10 adults per group.[36] Statistics New Zealand 2017 regional average wage rates for Māori were used since, as above, festival attendees predominantly self-reported as being Māori. The hourly wage rate averaged across all sub-regions was NZ$25.18, and ranged from NZ$22.28 to NZ$29.66. Hence the assumed travel time cost per hour of travel time averaged $8.39/adult, or $83.90 per assumed average-sized visitor group

[36] Lupi et al. (2020) recommend using between 33% and 50% of hourly income when estimating travel time costs.

of 10 adults.

The total travel cost used in our model for sub-region j, combining distance-based transport costs and time-based travel time costs per visitor group to and from the 2017 Te Matatini festival venue in Hastings, is finally estimated as:

$$TTC_j \equiv Total\, travel\, cost_j = Transport\, cost_j + Travel\, time\, cost_j \tag{10}$$

These estimated total travel costs range from NZ\$32/group for Hastings through to NZ\$5,337/group for Invercargill, and average NZ\$1,941/group.

Of the 29 sub-regions for which there were no visitor groups captured in the 2017 Te Matatini survey, 20 of those sub-regions were in the South Island. Conversely, the sub-region with the most visitor groups is Hastings, the hosting sub-region. All other things being equal, these are as expected – the greatest visitor group count is from the sub-region for which travel times and transport costs are lowest. Conversely, the sub-regions with the lowest visitor group counts are largely those for which travel times and transport costs – including inter-island ferry time and transport costs – are the greatest.

4.3 Demographics

Finally, Territorial Authority (TA) and Auckland Local Board (ALB) level 2018 Census data published by Statistics New Zealand was used to compile sub-regional demographic data. These include demand shifters like median income, and other potentially relevant explanatory variables such as sub-regional unemployment rates, rates of speaking te reo Māori, educational attainment levels, etc (a full list is given in Table 1 below). Where a given TA or ALB was shared across multiple sub-regions, the relevant Māori adult population figures were split equally among those sub-regions, while remaining variables were simply replicated across those sub-regions.[37]

4.4 Summary

Table 1 provides summary statistics on our dependent and explanatory variables. Having data for 100 sub-regions, our sample size is $J = 100$.

Our dataset is neither strictly a random sample based on on-site sampling, nor a random sample from the general population. The former has truncated zeros since only visitors are sampled. Conversely, the latter samples (possibly

[37]Conversely, the North Shore sub-region in Auckland was represented by combining data for the Kaipatiki and Devonport-Takapuna ALBs.

Table 1: Summary Statistics for Visitor Group Size Models Sub-Regional Dataset

Variable	Min.	Max.	Mean
Visitor groups (dependent)	0	228*	19.6
Total travel cost	32	5,337	1,941
Māori adult population	471	30,317	5,161
Median age	29.1	53.6	41.7
% Under 15	9.4	24.2	19.7
% 65 or over	7.9	31.0	18.5
% Māori	5.3	65.7	21.0
% Te reo speakers	1.0	23.9	5.2
% With disabilities	4.7	17.3	12.2
% Does not own home	23.7	50.9	29.0
% No qualifications	4.2	25.0	16.9
% Bachelor degree or higher	5.5	42.0	13.5
Median income (NZ$000)	20.6	42.7	30.2
% Unemployed	0.9	7.7	3.0
% Professional	4.3	23.8	9.2
% Labourer	2.9	13.7	7.7
% No vehicle	0.4	9.8	1.9
% No telecommunications	0.2	0.9	0.4
% Damp home	2.8	10.4	6.8
% Mouldy home	1.7	8.0	5.2

Notes: Sample size is $J = 100$. In February 2017, NZ$1.00 = US$0.72. * See discussion in text.

excess) zero counts, but can be costly to implement if visitor rates are low, requiring large samples to achieve sufficient visitor numbers for estimation. Instead our dataset is a hybrid of the two, seeking to replicate, as closely as possible, an aggregate population-level dataset of the sort used in Hellerstein (1991). We maintain the assumption that the data are sufficiently robust and representative to illustrate the differences between the modelling approaches we present, and leave it to future research to address any sampling issues that remain.

5 Results

5.1 Demand Models

Table 2 presents the results of Poisson, Quasi-Poisson and Negative Binomial variants of our naive calibration model, and compares them with the results of our Poisson zonal reference model.The estimated coefficients of the Poisson and Quasi-Poisson models are identical, although estimated standard errors and hence significance levels vary considerably between the two models. The dispersion parameter in the Poisson model is restricted to be unity, while it is unrestricted in the Quasi-Poisson model (Zeileis et al. (2008)). The estimated mean function is the same in each case, explaining why the estimated coefficients are identical in the two models.

Since the dispersion parameter in the Quasi-Poisson case is greater than unity, this confirms that over-dispersion is present in our data, and hence that the Poisson model's assumptions are violated. The apparently high significance levels reported for the Poisson model should therefore be disregarded, as indicated by the fewer significant coefficients in the Quasi-Poisson case. That said, importantly, the coefficient on total travel cost is highly significant in the Quasi-Poisson model as well as the Poisson model, and negative as expected (the greater the total travel cost, all other things being equal, the lower the demand for group visits to Te Matatini).

The Zonal Poisson model uses the Quasi-Poisson model's parameter estimates as the starting values for its maximum likelihood search procedure. The model could not be estimated using the `NR`, `NM` or `SANN` search methods, but could be estimated using the `BHHH` method. It too produces the same estimated coefficients as the Poisson and Quasi-Poisson models, being within search tolerance in its first two iterations.

Table 2: Results of Naive Calibration and Reference Demand Models

	Naive Calibration Model						Reference Model	
	Poisson		Quasi-Poisson		Negative Binomial		Zonal Poisson	
Intercept	8.97266	***	8.97266		3.20392		8.97266	***
	(2.62164)		(8.15752)		(9.68882)		(0.00000)	
Total travel cost	-0.00066	***	-0.00066	***	-0.00066	***	-0.00066	***
	(0.00005)		(0.00014)		(0.00013)		(0.00000)	
Māori adult population	0.00008	***	0.00008	***	0.0001	***		
	(0.00001)		(0.00002)		(0.00002)			
Median age	0.03579		0.03579		0.01696		0.03579	***
	(0.04598)		(0.14306)		(0.12962)		(0.00000)	
% Under 15	0.02366		0.02366		-0.04875		0.02366	***
	(0.05727)		(0.17821)		(0.20827)		(0.00000)	
% 65 or over	-0.12872	*	-0.12872		-0.18199		-0.12872	***
	(0.05657)		(0.17604)		(0.14967)		(0.00000)	
% Māori	-0.07131	***	-0.07131		-0.06175		-0.07131	***
	(0.01599)		(0.04976)		(0.05047)		(0.00000)	
% Te reo speakers	0.12874	***	0.12874		0.20462	.	0.12874	***
	(0.03376)		(0.10503)		(0.11599)		(0.00000)	
% With disabilities	0.13346	.	0.13346		0.25559		0.13346	***
	(0.07572)		(0.2356)		(0.21817)		(0.00000)	
% Does not own home	-0.04214		-0.04214		0.01621		-0.04214	***
	(0.02907)		(0.09047)		(0.09083)		(0.00000)	
% No qualifications	-0.29429	***	-0.29429	.	-0.0745		-0.29429	***
	(0.0488)		(0.15185)		(0.15314)		(0.00000)	
% Bachelor degree or higher	-0.24908	***	-0.24908	.	-0.10926		-0.24908	***
	(0.04711)		(0.14659)		(0.12463)		(0.00000)	
Median income (NZ$000)	-0.08141	***	-0.08141		-0.03629		-0.08141	***
	(0.02349)		(0.07309)		(0.06428)		(0.00000)	
% Unemployed	0.12251		0.12251		0.12449		0.12251	***
	(0.08097)		(0.25194)		(0.27129)		(0.00000)	
% Professional	0.37912	***	0.37912	.	0.31385	.	0.37912	***
	(0.06917)		(0.21523)		(0.18923)		(0.00000)	
% Labourer	0.17783	***	0.17783	.	0.12311		0.17783	***
	(0.02893)		(0.09002)		(0.09289)		(0.00000)	
% No vehicle	0.16963	*	0.16963		-0.02281		0.16963	***
	(0.08043)		(0.25027)		(0.28218)		(0.00000)	

Table 2 (cont'd): Results of Naive Calibration and Reference Demand Models

	Naive Calibration Model					Reference Model	
	Poisson		Quasi-Poisson		Negative Binomial	Zonal Poisson	
% No telecom-munications	1.2899	*	1.2899		-0.87714	1.2899	***
	(0.54164)		(1.68538)		(1.59488)	(0.00000)	
% Damp home	-0.17828		-0.17828		-0.34896	-0.17828	***
	(0.12406)		(0.38603)		(0.33669)	(0.00000)	
% Mouldy home	0.12719		0.12719		0.3876	0.12719	***
	(0.13934)		(0.43358)		(0.38291)	(0.00000)	
AIC	1072.1				625.1		
Dispersion Parameter	1^		9.68		1.728		

Notes: Dependent variable is sub-regional number of average-sized groups visiting 2017 Te Matatini festival. Naive calibration models estimated using `glm` package in `R`. Zonal Poisson model estimated using `maxLik` package in `R`, using `BHHH` search method. Significance levels are 0.1% "***", 1% "**", 5% "*", 10% ".". ^ Dispersion parameter restricted to be unity.

The fact that this model – despite apparently having a different formulation – produces the same parameter estimates as the naive calibration models, is also perhaps to be expected. The calibration models include Māori adult population as an explanatory variable, and Haab and McConnell (2002, p. 182) explain how including this variable can be used to estimate the zonal Poisson model without needing to directly maximise the associated log-likelihood function.

Finally, the Negative Binomial model produces coefficient estimates that are not identical to those of the Poisson-based models. As for the Quasi-Poisson model, its estimated dispersion parameter is greater than unity, confirming that over-dispersion is present in our data, and hence that the simple Poisson model's assumptions are violated. Notably, however, its estimated coefficient on total travel cost is identical to that in the other three models.

Table 3: Results of Binomial Logit Demand Model

	NR		NM		SANN		BHHH	
Total travel	-0.00073	***	-0.00073	***	-0.00092	***	-0.00115	***
cost	(0.00003)		(0.00003)		(0.00004)		(0.00000)	
Median income	-0.14607	***	-0.14604	***	-0.07312	***	-0.1281	***
(NZ$000)	(0.00342)		(0.00342)		(0.00406)		(0.00013)	
% Professional	0.18722	***	0.18713	***	-0.00605	***	0.49529	***
	(0.00823)		(0.00823)		(0.01118)		(0.00035)	
Log-Likelihood	-7,857		-7,857		-8,104		-11,627	

Notes: Dependent variable is sub-regional number of average-sized groups visiting 2017 Te Matatini festival. Significance levels are 0.1% "***", 1% "**", 5% "*", 10% ".".

This provides reassurance that – supposing such models appropriately reflect the data generating process – the estimated total travel cost coefficient, which is key for WTP estimation, is robust to choice of modelling approach. However, as discussed earlier, these unrestricted models allow for visitor groups to make any number of visits to Te Matatini, when our data reflects visitor groups making a binary choice to either visit the festival or not. Hence we turn to the results of our novel Binomial Logit model, which better reflects this decision-making process.

Table 3 presents results for our Binomial Logit demand model. It was not possible to estimate the model using the full set of explanatory variables, so instead it was estimated with an illustrative subset of variables. Income was included despite not apparently being significant in the preceding models since it represents a commonly-used demand shifter.[38] Results are presented for the four search methods tried when maximising the log-likelihood (7).

As can be seen from the table, the estimated total travel cost coefficient varies significantly depending on which search method is used to maximise the log-likelihood. However, since we are estimating the same model in each case, with the same dependent and independent variables, we can identify the preferred search methods based on log-likelihood values. This indicates that the NR and NM methods are to be preferred, since they jointly achieve the highest log-likelihood value of the four approaches.

[38] For example, see Hellerstein (1991).

Notably, the NR and NM approaches each estimate the total travel cost coefficient to be -0.00073. As for the earlier models, the coefficient is both highly significant, and negative (indicating an inverse relationship between total travel cost and demand for group visits to Te Matatini). However, in contrast to those earlier, unrestricted count models, the Binomial Logit model – which restricts visitor groups to either visit Te Matatini or not – estimates this coefficient to be more negative than the -0.00066 estimated using the earlier models.

We now show what difference these modelling approaches make to estimated WTP for access to the 2017 Te Matatini kapa haka festival.

5.2 Estimated WTP for Access to the 2017 Te Matatini Festival

Following Haab and McConnell (2002, pp 166-167), visitor group WTP for access to the 2017 Te Matatini festival for our unrestricted (i.e. naive calibration and zonal Poisson) models is estimated as:

$$WTP^{U}_{Group}\left(Access\right) = -\frac{\bar{n}}{\hat{\beta}^{U}_{TTC}} \tag{11}$$

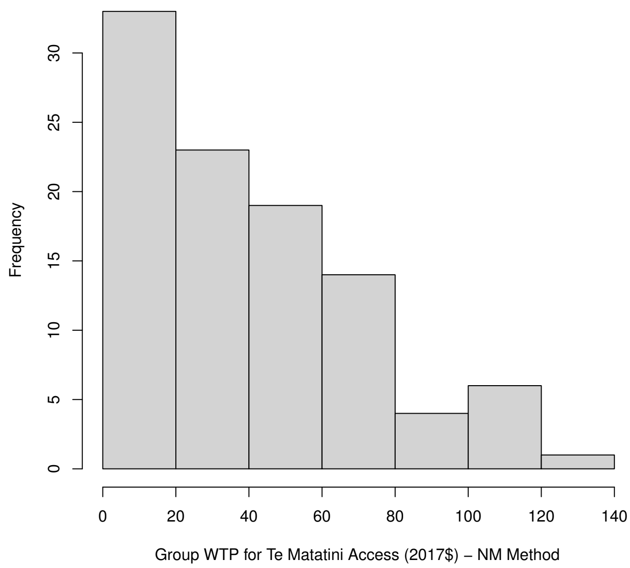
where $\bar{n} = \frac{1}{J}\sum_{j=1}^{J} n_j$, and $\hat{\beta}^{U}_{TTC}$ is our estimated total travel cost coefficient from the unrestricted demand models. As explained by Haab and McConnell, WTP estimates for Poisson models – as for Negative Binomial models – have a mean-preserving property with the result that either the mean of expected group visits or mean of observed group visits can be used in the denominator. From Table 1, $\bar{n} = 19.06$, and from Table 2 we have $\hat{\beta}^{U}_{TTC} = -0.00066$. This implies that $WTP^{U}_{Group}\left(Access\right) \approx NZ\$29,000$ per group, or $NZ\$2,900$ per adult in 2017.

Interpreting our logit probability (4) as the expected demand of a representative group for attending the 2017 Te Matatini festival, the group-level WTP for access in the restricted Binomial Logit demand model for sub-region j is consumer surplus estimated as follows:[39]

$$WTP^{BL}_{Group,j} = \int_{TTC_j}^{\infty} \frac{exp\left(x_j\hat{\beta}^{BL}\right)}{1+exp\left(x_j\hat{\beta}^{BL}\right)} dTTC = \frac{ln\left(1-\hat{P}\left(y_{t,j}=1\right)\right)}{\hat{\beta}^{BL}_{TTC}} \tag{12}$$

[39]This requires $\hat{\beta}^{BL}_{TTC} < 0$, and is the same result as in Freeman et al. (2014, pp 282-283) with the Binomial Logit model interpreted as a special case of the more general Multinomial case presented there.

Figure 2: Distribution Across Sub-Regions of Estimated Group-Level WTP for Access to 2017 Te Matatini Festival (2017NZ$)



where $\hat{\beta}^{BL}$ is our vector of estimated demand coefficients (including $\hat{\beta}^{BL}_{TTC}$) using the Binomial Logit model and, as before, x_j is our row vector of explanatory variables for sub-region j (including $TTCj$). From Table 3 (using either of the preferred `NR` and `NM` estimates), we have $\hat{\beta}^{BL}_{TTC} = -0.00073$, and $\hat{P}\left(y_{t,j} = 1\right)$ is our estimated probability of a representative group in sub-region j choosing to attend the 2017 Te Matatini festival, calculated as:

$$\hat{P}\left(y_{t,j} = 1\right) = \frac{exp\left(x_j\hat{\beta}^{BL}\right)}{1 + exp\left(x_j\hat{\beta}^{BL}\right)} \tag{13}$$

Figure 2 illustrates the distribution of group-level WTP for access across the 100 sub-regions in our sample, estimated using the Binomial Logit approach. The maximum group-level WTP for access to Te Matatini is estimated to be NZ\$125.62. The mean across all sub-regions is estimated to be NZ\$39.67.

Table 4: Summary of Estimated WTP for Access to 2017 Te Matatini Festival (2017NZ$)

	Reference Model	Binomial Logit	
Travel time cost as % of average wage	33%	33%	50%
Group (average)	29,000	39.67	51.56

Notes: WTP estimates for Binomial Logit based on `NM` coefficient estimates.

Finally, we note that these WTP estimates were derived on the basis of travel time costs that were measured as one third of hourly income. Best practice recommendations provided by Lupi et al. (2020) include measuring travel time costs as high as half of hourly income.

Table 4 summarises the preceding results, and augments the Binomial Logit WTP estimates by including their values when estimated using half of hourly income to measure travel time costs. As can be seen, this raises the average group WTP from NZ$39.67 to NZ$51.56. These new WTP estimates are approximately 30% higher than the previous ones based on the lower value of travel time costs.

6 Conclusions

In this study we apply TCMs, a well-established revealed preference technique for undertaking NMVs in both environmental and cultural economics, to value a particular aspect of Māori culture. Specifically, we value one aspect of kapa haka, the Māori performing arts – namely, participation at the Te Matatini national kapa haka festival held in Hastings in February 2017.

An important feature of this approach is that it relies on the revealed preferences of Te Matatini attendees to infer their WTP for access to the festival. This is achieved by relating variation in the sub-regional demand of visitor groups for attending the festival with variation in the transport and travel time costs they incur when visiting the festival from different sub-regions of New Zealand. As expected, all other things being equal, that demand is inversely related to total travel cost. Our approach has not distinguished the additional costs incurred by performers at the 2017 festival relative to those of spectators and supporters, which is likely to have caused our WTP to be underestimated.

Also, because we have valued just one aspect of the use value of kapa haka (see Figure 1 for the overall valuation scheme), this study says nothing about the other cultural values attaching to kapa haka. Specifically, it says nothing about the use value of those who participate in kapa haka – whether as performers, spectators, or supporters – outside of the biennial Te Matatini festivals (e.g. at regional festivals or schools, on marae (traditional communal meeting places), etc). It also says nothing about the option, bequest and existence values that also attach to this prominent aspect of Māori culture. Hence, at most, this study captures just one component of the overall cultural value of kapa haka, and provides only a lower bound estimate of its value.

We have shown that existing approaches for implementing TCMs are relatively robust to mis-specification, in that they produce comparable estimates of the marginal effect of total travel cost on demand. However, we also show that estimates of users' WTP for access to the 2017 Te Matatini festival is sensitive to how demand for group visits to the festival is specified. Our novel Binomial Logit specification of demand, which is better suited to our specific valuation context, produces WTP estimates that are an order of magnitude lower than other, unrestricted models that fail to account for the specific decision context confronting potential visitors to Te Matatini festivals.

We leave it to future research to address limitations of this study, and to more comprehensively estimate the value of kapa haka. To improve the estimation of TCMs for valuing Te Matatini festivals, it would be desirable to sample randomly from the entire population, in order to better understand how decision-makers choose between attending the festival and not attending. To better understand how potential visitors to Te Matatini evaluate different quality attributes of the festival, and possible alternatives to attending, it would be desirable to conduct stated choice experiments using random utility models, which currently represent the state of the art for NMV studies.

Importantly, such stated choice experiments could be used to estimate not just kapa haka use values, but also bequest and existence values in particular. Properly constructed, they could shed light on how different sub-populations assign different valuations to different aspects of the use and non-use values of kapa haka. Such further research would not only provide a more concrete assessment of the value of Te Matatini, but also of the wider cultural values attaching to kapa haka. This study points to how such further research could contribute to a better understanding of indigenous cultural values, and of Māori cultural values in particular.

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