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Valuing Historic Attractions Using Travel Cost Methods and Mobile Data

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Department for Culture Media & Sport

Valuing Historic Attractions Using Travel Cost Methods and Mobile Data

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1 Introduction

England's historic environment encompasses both tangible and intangible assets. Historic attraction sites, as key elements of this heritage, not only remind us of our history but also significantly contribute to the nation's economy. These sites possess historical, cultural, and economic value, yet their value is often underrepresented. Despite their importance, traditional market transactions often fail to reflect these sites' non-market and non-use values, especially as many are free-to-enter or operated by charities.

Recognising the need to quantify this additional value, Historic England, supported by the Culture and Heritage Capital (CHC) programme and the Department for Culture, Media and Sport (DCMS), is conducting an innovative study using mobile analytical data. This study aims to inform stakeholders, including government bodies, heritage organisations, and cultural economists, about the feasibility of using mobile data in assessing the non-market value of historic sites through the Travel Cost Method (TCM). The primary goal of this report is to demonstrate that mobile analytical data is a suitable sampling methodology, providing evidence for its application across both the heritage and cultural sector.

TCM is a revealed preference technique based on observed behaviour rather than hypothetical preferences. Approved under HM Treasury's Green Book, it is used to assess the non-market benefits of goods. By analysing visitors' willingness to incur travel costs, TCM offers insights into consumer surplus (CS) and the non-market values of cultural heritage sites. This approach captures part of the non-market value, reflecting the significance visitors place on these sites beyond ticket prices or market transactions.

While TCM is traditionally applied through surveys and interviews, this study proposes a significant methodological advancement by using mobile analytical data. This approach addresses the limitations of traditional surveys, especially for hard-to-assess historic sites, and enables a broader, more representative understanding of visitor behaviour. By establishing a cost-efficient method to estimate non-market values, this study could provide heritage organisations with a practical tool to justify funding applications, develop business cases for site preservation, and implement strategic planning for cultural asset management.

The study evaluates the quality of mobile analytical data by comparing it with English Heritage online booking data to validate the findings and assess their accuracy. This phased approach, starting with pay-to-enter sites, will provide a foundation for future applications to free-to-enter sites and other hard-to-quantify locations.

In addition to refining valuation methodologies, this project contributes to the broader discussion of the economic role of heritage in England. This is particularly timely, as English Heritage – now operating independently of government funding – faces critical business decisions. Understanding and giving weight to the additional non-market value of these sites could significantly influence investment strategies, ensuring sustainable preservation efforts.

Ultimately, this project seeks to establish mobile data as a viable tool for travel cost analysis, with potential applications across public, private, and third-sector cultural organisations. By aligning with the broader aims of the Culture and Heritage Capital programme, this study aims to articulate the value of culture and heritage in informed decision-making.

2 Culture and Heritage Capital programme

This research is funded through the Culture and Heritage Capital (CHC) Programme, led by the Department for Culture, Media and Sport (DCMS), which seeks to transform how the value of cultural and heritage assets is assessed. With a focus on robust appraisal and evaluation methods (Sagger and Bezzano, 2024), the CHC Programme aims to comprehensively value the economic, social, and cultural contributions of the creative, cultural, and heritage sectors. The programme's goal is to develop a formal approach to decision-making that combines economic methodologies with qualitative and quantitative evidence, providing a deeper understanding of culture and heritage's societal contributions and supporting more effective policymaking and investment.

A core objective of the CHC Programme is to help policymakers, public bodies, and private organisations make more holistically informed decisions by considering the long-term impacts of culture and heritage on wellbeing, happiness, and quality of life, alongside traditional economic measures. The programme aims to produce publicly available statistics, supplementary guidance, and eventually a Culture and Heritage Capital Account. These resources are designed to assist policymakers, researchers, and the public in understanding and advocating for the value of culture and heritage. The CHC programme stresses the need for a consistent method to capture and articulate the benefits of culture and heritage, addressing the historical challenge of underrepresentation in Social Cost-Benefit Analysis (Kaszynska et al., 2022).

Within this broader context, the Travel Cost Method (TCM) serves as a revealed preference method to assess the economic value of cultural heritage by analysing visitors' travel costs and the associated consumer surplus. This empirical approach supports the CHC's goal of developing a robust evidence base for informed policymaking. Traditionally applied through surveys and interviews, TCM is innovatively expanded in this study by incorporating mobile analytical data. This integration enhances precision, reduces data collection costs, and allows for broader and more representative sampling of visitor behaviour, addressing some limitations of traditional methodologies.

The use of mobile data within TCM not only reinforces the CHC Programme's objectives but also opens new avenues for understanding the relationship between people and heritage. The knowledge gained from applying TCM can inform strategic decisions regarding funding allocation, preservation efforts, and the enhancement of visitor experiences, contributing to the sustainable development of the heritage sector.

3 Literature Review

Cultural capital includes assets that hold both cultural and economic value. Throsby (2000; 2019) highlights the duality, noting that economic value includes both market use values, benefits individuals receive from engaging with cultural goods (e.g., visiting a heritage site), and non-market benefits including educational benefits recreational benefits, wellbeing and more, that contribute to societal welfare (Báez-Montenegro et al., 2012). Non-use values, like existence and bequest value, are also integral, as they reflect the importance individuals place on cultural goods even without direct engagement. However, these non-market and non-use values often go unaccounted for in conventional economic assessments.

Cultural heritage can often be viewed as a public good, contributing to public welfare. Historic attraction sites such as historic buildings and landscapes, contribute to public welfare, including historical significance, aesthetic appeal, social value, spiritual meaning and shared communal experiences (Throsby, 2001). Viewed as public goods, these sites' benefits are not easily quantified in economic terms. Therefore, valuing heritage assets poses challenges, as conventional market transactions fail to capture their full spectrum of social and cultural impact.

The challenge in valuing cultural heritage lies in capturing its market, non-market, and non-use values in a way that allows for meaningful comparisons, such as expressing them in monetary terms (£), to better estimate their broader social and economic impact (Mendes, 2016; Sagger and Bezzano., 2024; Kaszynska et al., 2022). This makes non-market valuation techniques essential to represent both economic and societal contributions of heritage more comprehensively.

Non-market valuation methods can be divided into stated preference and revealed preference methods. Stated preference methods, including contingent valuation and choice modelling, estimate value by directly asking individuals, capturing both non-market and non-use benefits. Revealed preference techniques, such as hedonic pricing and travel cost methods (TCM), involve inferring the price or value which individuals place on something by examining their actual behaviour. These are only able to measure the non-market benefits as they are based on actual users' behaviours. Each approach has its strengths and limitations, with TCM particularly suited for understanding visitor behaviour at cultural and recreational sites.

TCM estimates a site's value based on the total costs incurred by visitors, including travel expenses, time costs, and entrance fees. Unlike stated preference methods, which rely on hypothetical scenarios, TCM analyses actual choices made by individuals. Studies, such as those by Hotelling (1949) and Clawson and Knetsch (1966), established the theoretical framework for TCM, demonstrating its applicability in valuing public goods. Approved by HM Treasury’s Green Book, TCM remains a cornerstone of non-market valuation, most notably used in natural capital approaches.

Various adaptations of TCM have emerged, such as the individual travel cost method (ITCM) and the zonal travel cost method (ZTCM). The ITCM examines the individual demand function as a function of travel cost, considering the travel costs incurred by individual visitors, making it suitable for analysing detailed visitor behaviour and preference. Ceccacci et al. (2024) applied ITCM to examine the non-market value of fishing harbours in Europe using granular survey data that includes individual demographic variables. ZTCM, on the other hand, examines the relationship between visit frequency from a given zone and average travel costs, as shown by Fleming and Cook (2008). Each of these methods has its advantages and disadvantages. The ZTCM is advantageous for its simplicity and lower data requirements, but it may lack detail and accuracy, due to aggregation of preferences to an entire geographic area. The ITCM provides more granular insights but requires extensive data collection.

While TCM has been widely used within natural capital valuation, and for cultural heritage sites globally, its application in the UK remains limited. Poor and Smith (2004) estimated the benefits of St. Mary’s City of Maryland using a zonal travel cost model, finding individual consumer surplus between $8.00 and $19.26 annually. Similarly, Jones, Yang, and Yamamoto (2020) evaluated the impact of World Heritage Site inscription on Mount Fuji's recreational value, using data from summer surveys between 2008 and 2013. They found stable demand, with GIS analysis identifying changes in visitor clusters.

Voltaire et al. (2016) applied TCM to Mont-Saint-Michel, surveying 1,194 visitors in 2011. The study found a significant consumer surplus and assessed parking fees' impact on visitor numbers. Likewise, Torres-Ortega et al. (2018) estimated the National Museum of Altamira's annual economic value at 4.75 to 8 million Euros, based on 1,067 visitor responses over six months.

Recent innovations in data collection, such as the use of mobile analytical data, can transform the non-market valuation. However, research remains sparse and is, to the best of our knowledge, yet to be applied to heritage or cultural assets. Notably, Dai et al. (2022) explored using mobile signal data to estimate a zonal travel cost model of a wetland in China. They highlight that mobile analytical data, compared to that of traditional survey-based methods, can provide a much larger sample of visitors and these visitors can be tracked over large intervals of time, potentially reducing any bias associated with collecting samples at specific points in the year. Although this study utilises a large sample of visitors, the granularity of their analysis covers a vastly larger geographical area compared to this study. Jaung and Carrasco (2020) also used mobile signal data to analyse the economic benefits of urban protected areas and parks in Singapore. This study, methodologically, highlights the potential use of mobile data to analyse traditionally hard to measure sites. However, these studies also reveal limitations, particularly the absence of counterfactuals to validate data accuracy and potential biases inherent in mobile signal data.

Building on this emerging field, the present study employs GPS data as a methodological innovation to address some of these limitations. GPS data offers higher spatial accuracy and greater precision in tracking visitor behaviour compared to mobile signal data. By applying GPS-derived mobile analytical data to English Heritage sites, this study aims to refine the use of TCM for valuing cultural heritage, contributing to a more comprehensive understanding of the economic and societal impacts of these sites by understanding their non-use value through TCM. This study also uses visitor data collected during the COVID-19 pandemic, when online booking was mandatory for all English Heritage (EH) sites, allowing us to compare the findings with GPS data to assess the feasibility and accuracy of this innovative approach.

Through these contributions, this study not only bridges gaps in the application of TCM but also seeks to reduce the time and costs associated with traditional data collection methods. The potential implications extend beyond English Heritage, offering a robust framework for valuing cultural assets more broadly and supporting evidence-based decision-making in the heritage sector. In the next phase of Historic England’s CHC research programme, we will be seeking to apply this approach to a broader range of sites.

4 Data

4.1 English Heritage Trust Data

The dataset provided by English Heritage Trust (EHT) forms the counterfactual to our research data, offering in-depth information on heritage sites, including visitor numbers, opening times, average admission costs and estimated percentage of visitors travelling by car. Additionally, online bookings during the COVID-19 period have provided a valuable source of detailed visitor data for English Heritage sites. This unique context provides a much larger dataset than typically seen in the travel cost literature.

The data used includes:

- Admissions numbers, origin data at 4-digit postcode level, month and year visited.
- Insights from site-specific features (e.g., mode of transport to the site) that influence visitation patterns.
- Specific admission fees that are associated with each site.

4.2 Mobile Analytical Data

The mobile analytical data comes from the Huq platform, introducing a novel aspect to our sampling methodology. This data set comprises anonymised, real-time GPS data that comes from mobile applications.

The mobile data enables an alternative TCM analysis by providing:

- Data on the number of individuals who enter a geospatial boundary, situated around a historic attraction site for any given period.
- Origin data and dwell time data.

This mobile analytical data approach aims to validate the TCM findings derived from English Heritage data, offering an alternative sampling method that can be applied for other historical attractions sites, and provide a potential path for significant expansion of travel cost methods both in the field of heritage, and in the cultural sphere.

Table 1: Visitor count estimates for English Heritage and Huq mobile analytical data (000s).

Site	EH (2020/21)	Huq (2020/21)	EH (2021/22)	Huq (2021/22)	EH (2022/23)	Huq (2022/23)
Audley End House and Gardens	83	45	168	143	165	95
Beeston Castle	34	59	54	76	51	44
Belsay Castle	38	40	65	44	66	60
Bolsover Castle	40	46	85	95	90	92
Brodsworth Hall	61	47	96	52	99	51
Dover Castle	94	92	172	171	233	267
Eltham Palace	38	38	104	109	127	147
Farleigh Castle	5	5	18	22	18	27
Furness Abbey	5	19	11	15	11	44
Goodrich Castle	22	22	44	44	43	38
Kenilworth Castle	63	48	114	104	118	74
Mount Grace Priory	18	21	37	65	48	42
Rievaulx Abbey	18	35	49	82	52	75
Stokesay Castle	9	3	31	13	36	29
Whitby Abbey[1]	53	125	162	236	182	233

4.3 ONS Demographic Controls

Demographic information is gathered from numerous sources. We use demographic data from the ONS and Census. This strategy allows us to explore the impact of various demographic factors on travel behaviours and heritage site valuations, enhancing the precision of our consumer surplus estimations.

1 Very large differences are observed in the visitor counts for Whitby Abbey, this is linked to a relatively significant change in boundaries. In our analysis, we choose to use the original boundaries and then explore the impacts in the robustness section (section 8).

5 Methodology

5.1 Geographical Detail and MSOA Utilisation

The research utilises Middle Layer Super Output Area (MSOA) spatial boundaries provided by the ONS, providing granularity finer than that typically applied in zonal travel cost method studies. This addresses numerous issues that surround zonal travel cost methods such as the relevance of control variables, high variation of distance within zone and differences between zones. However, it also presents challenges, such as potential data sparsity.

5.2 Algorithm

To address potential biases in regions with sparse data, our methodology includes the development of an algorithm designed to improve the accuracy of travel cost estimations. The advantages of both the English Heritage and Huq mobile analytical datasets are the higher level of granularity we can observe compared to traditional surveying methods. This allows us to use a lower level of spatial location.

However, in doing so we risk increasing the chances of areas with zero data biasing our results. Beal (2000) argues that removing these zero-visit zones in the regression will truncate the data and upwardly bias consumer surplus calculations. On the other hand, including them can skew results in the opposite direction. They recommend merging zero-visit zones with nearby zones that have visitors.

Using an algorithm developed by Historic England, we merge our data points with zeros based on the proximity of the population-weighted centroid to MSOAs that share a border, as well as the average income level of the MSOA. This approach aims to ensure representativeness and reliability across diverse geographical settings, improving the overall quality of our analysis.

In terms of the underlying data the English Heritage data was more granular than the GPS data. This is due to:

1. The data is available for the number of visitors by month, year, and by 4-digit postcode level.
2. The data does not require extrapolation from the raw data source.
3. EHT data is available for all individual visits at 4-digit postcodes, whereas mobile analytical data is only available for 4-digit postcodes with a minimum number of visitors for anonymity purposes, to present at 4-digit postcode.

This resulted in more individual data points for the English Heritage data as shown in Table 2, thus when mapped to an MSOA there were more data entries and a higher number of geographic zones. The result of this is when we merge MSOA's to remove 0s (as described above), the number of merges is larger for Huq. This can be seen in Figure 1 below, where red indicates a zone with 0 visits and blue indicates a zone with more than 0 visits. In Section 7, an alternative method of utilising the mobile analytical data is discussed.

Table 2: Number of geographical zones after merging.

Site	Zones pre-merge	Zones post-merge EH	Zones post-merge Huq
Audley End	2178	1250	271
Belsay Hall	385	243	105
Eltham Palace	2343	1263	919
Mount Grace Priory	1175	689	486
Stokesay Castle	1025	500	153

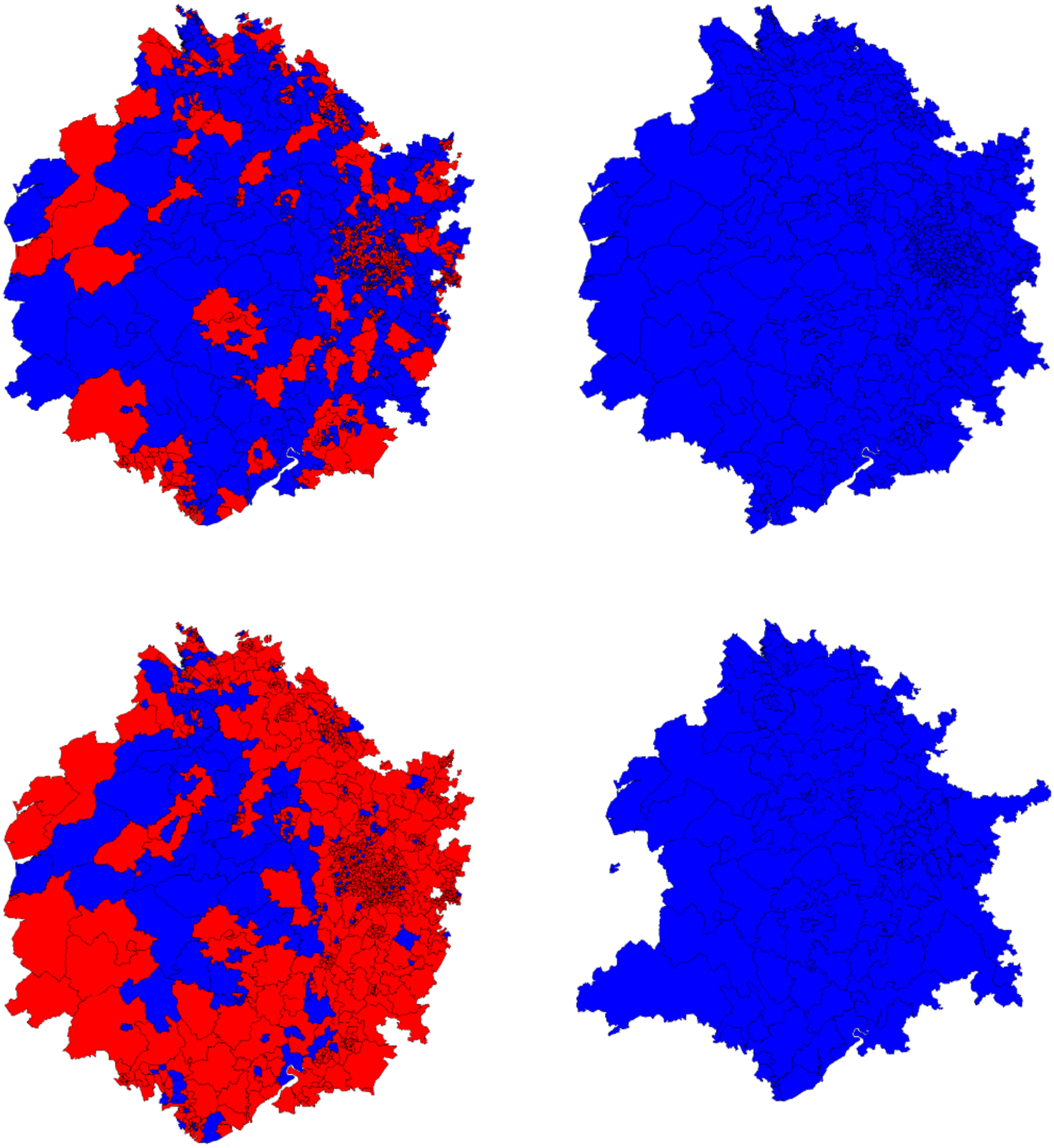

Figure 1: Comparison for Stokesay Castle.
Top left: pre-merge EH data. Top right: post-merge EH data. Bottom left: pre-merge Huq data. Bottom right: post-merge Huq data.

5.3 Opportunity Cost

Opportunity cost is a significant component in the estimation of travel costs within a TCM. It represents the value of the time that visitors forego to travel to heritage sites. Accounting for opportunity cost ensures a more accurate calculation of total travel expenses.

We trialled different forms of opportunity cost to determine the most appropriate measure for our analysis:

Opportunity cost 1: 20% of people's average wages in the geographical unit

Opportunity cost 2: 50% of people's average wages in the geographical unit

Opportunity cost 3: 100% of people's average wages in the geographical unit

Opportunity cost 4: Krekel and MacKerron (2023) opportunity cost of time, which is a fixed value of £8.40/hour.

The rationale for this range is that individuals may value their time differently across different incomes, and individuals may also have different levels of substitution on how they value their leisure time to their work time. Given the scope of this report, we do not aim to identify the most suitable opportunity cost; however, a decision is made to use opportunity cost 4 in our main analysis due to several reasons discussed in Section 5.5, Section 7, and Appendix A.[2]

5.4 Travel Cost

To calculate the average travel cost for visitors from each zone, we combine admission fees with estimated travel expenses. This is done by using the population-weighted centroid of the MSOA and estimating both the distance and the estimated time it would take to travel from the centroid to the historic attraction.

- We calculate the estimated fuel cost by multiplying the distance measured in kilometres, by £0.12 per kilometre.
- In addition, we add an opportunity cost for their time. This ranges between 20 to 100% of their estimated income, based on ONS estimated incomes for the MSOA. In addition, we present an estimation utilising Krekel and Mackerron (2023) approach to estimating the value of time dependent on experience, in this case, the value of time spent commuting (£8.40).

2 Unsurprisingly, the level of the opportunity cost has a significant impact on the estimated total economic value and consumer surplus.

5.5 Econometric Zonal Travel Cost Method

The Zonal Travel Cost Method (ZTCM) employs an econometric framework utilising distinct zones based on the different geographic areas from which visitors travel from. This method allows for the estimation of a site's demand function by analysing the relationship between the number of visitors from each zone (adjusted for the zone's population) and the travel cost to reach the site. We use the following model specification:

$$y_i = f(C_i, X_i; \beta, \epsilon)$$

Our dependent variable of interest is y_i the number of visits from zone i divided by that zone's population. The independent variables are the travel cost from zone i to the heritage site, represented by C_i, and the average income of each zone's residents, I_i. Lastly, ε represents the idiosyncratic error, which in this estimation has been made robust to heteroskedasticity.

Linear, log-linear, linear-log and log-log specifications were estimated using ordinary least squares, with the following functional forms:

Table 3: Model specifications.

Specification	Functional form
Linear	$y_i = \beta_0 + \beta_1 C_i + \beta_2\, log\, I_i + \epsilon_i$
Log-linear	$\log\ y_i = \beta_0 + \beta_1 C_i + \beta_2\ \log I_i + \epsilon_i$
Linear-log	$y_i = \beta_0 + \beta_1 \log \mathrm{C_i} + \beta_2 \log \mathrm{I_i} + \epsilon_i$
Log-log	$\log \mathrm{y_i} = \beta_0 + \beta_1 \log \mathrm{C_i} + \beta_2 \log \mathrm{I_i} + \epsilon_i$

We compared each model's R^2 value; information criteria scores; looked at the relationship between English Heritage and Huq results; and investigated skewness in the model residuals. We found that the log-log functional form performed well across model fit scores and had the most comparable results between the English Heritage and Huq data.

Furthermore, our investigation into residual skewness found that only models with logarithms of the cost variable could appropriately smooth the data, this can be seen graphically in Appendix B. The log-log model was concluded as the model to move forward with, and all subsequent results relate to this specification. The results of the remaining three functional forms can be found in Appendix G.

6 Results

Ordinary least squares (OLS) regression is applied to both English Heritage data and Huq mobile analytical data under 16 different specifications. These specifications combine four functional forms (Linear, Log-Linear, Log-Log, and Linear-Log) with four opportunity cost scenarios (20%, 50%, 100% of income, and a fixed cost of £8.40/hour). We present all specifications and opportunity cost variations in Appendix C. Log-log functional form with a fixed opportunity cost of £8.40 was chosen as the main point of analysis, and OLS regression results under this specification are provided below.

Table 4: Regression Results for English Heritage and Huq Mobile Analytical Data for log-log specification. Standard errors are in brackets.

Site	Cost (EH)	Income (EH)	Cost (Huq)	Income (Huq)
Audley End	-7.7271 *** (0.213)	-0.4242 ** (0.206)	-6.5451 *** (0.489)	-3.7324 *** (0.682)
Belsay Hall	-4.9152 *** (0.321)	2.4955 *** (0.515)	-4.3615 *** (0.401)	0.401 (0.741)
Eltham Palace	-4.621 *** (0.156)	0.281 (0.217)	-4.4409 *** (0.156)	-2.8038 *** (0.253)
Mount Grace Priory	-4.2362 *** (0.153)	3.1201 *** (0.276)	-3.6926 *** (0.153)	-0.421 (0.303)
Stokesay Castle	-3.5026 *** (0.204)	2.3022 *** (0.342)	-4.5145 *** (0.406)	-2.6300 * (1.074)
Dover Castle	-4.3866 *** (0.190)	0.6785 ** (0.277)	-7.3756 *** (0.281)	-0.653 (0.491)
Goodrich Castle	-3.3236 *** (0.175)	3.1391 *** (0.267)	-3.6158 *** (0.217)	-1.5800 *** (0.378)
Furness Abbey	-3.1168 *** (0.214)	0.388 (0.841)	-4.6201 *** (0.211)	-1.107 (1.001)
Whitby Abbey	-2.4268 *** 0.235)	1.9964 *** (0.273)	-4.1737 *** (0.277)	0.312 (0.387)
Rievaulx Abbey	-4.1835 *** (0.209)	2.5019 *** (0.296)	-5.0119 *** (0.535)	-0.385 (0.723)

* p < 0.05, ** p < 0.01, *** p < 0.001, * indicates the significance

Looking across the sites using both English Heritage data and mobile analytical data, the cost variable is consistently significant and shows a negative relationship with the dependent variable, indicating that higher costs are associated with a reduction in visitor numbers per capita of the population. This consistent finding underscores the sensitivity of visitors to cost changes, regardless of the data source or model used.

Appendix C provides details on all four specifications. The differences between these models are more noticeable than those presented. For example, at Mount Grace Priory, the cost variable in the Linear model is estimated at -0.0012 in the English Heritage data, whereas in the mobile analytical data, it is -0.0002. These differences can be attributed to two main reasons. Firstly, the scale of the dependent variable is based on the number of visitors. From July 2020 to June 2021, the English Heritage online bookings data suggested 28,800 visitors as opposed to 8,800 visitors[3] in the mobile analytical data for Mount Grace Priory. This difference leads to higher coefficients in the English Heritage data, as a 1-unit increase in cost would have a greater effect on the dependent variable. Secondly, the mobile analytical data has a lower level of granularity, with larger geographic zones. This tends to increase the average values, introducing an upward bias on the coefficients for the mobile analytical data. The differences observed in the Log-Log models are less remarkable, -4.2362 compared to -3.6926.[4]

Direct comparison must be approached with caution, as the average of the dependent variable differs between the two datasets, with the mean being 0.00316 for English Heritage and 0.0012 for the mobile analytical data. The logarithmic variable changes the interpretation, thus a 1% increase in total costs would be estimated to cause a 4.2% (English Heritage) or a 3.7% (mobile analytical) decrease in visitor numbers respectively.

These results are also dependent in part on the choice of opportunity cost. While it is not the focus of this study to evaluate the suitable level to which opportunity cost should be attributed, Appendix C shows that by increasing the opportunity cost, we see a decrease in the expected impact of price rises on visitor rates.

To better compare the suitability of the models, analysing consumer surplus and consumer surplus per capita estimates is recommended. This approach provides a more comprehensive understanding of the economic impact and visitor behaviour across different heritage sites.

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3 This is later revised, as discussed in section 7.1 and section 8.3

4 This will be a consistent finding across our paper that when the dependent variable is log transformed, the value is more consistent and less susceptible to changes in specification.

7 Consumer Surplus

7.1 Methodology

Consumer surplus represents the welfare gain that consumers experience when they pay less than the maximum price they are willing to pay. For an individual, this is the difference between the current price and the maximum price at which they would still make the purchase. In the context of this research, consumer surplus reflects the scenario where the travel cost to a given English Heritage site becomes such that the consumer is no longer willing to travel.

The regression equation in Section 5.5 has a functional form that implicitly assumes the relationship between visitors and travel costs across each MSOA is uniform. Suppose our estimated relationship is such that:

$$\hat{y}_i = 0.2 - 0.3\, log\, C_i.$$

Where $i \in \{1, \dots, m\}$ indicates the MSOA, hereafter referred to as the zone. In this example, the coefficient -0.3 is uniform across all zones, implying that the impact of travel cost on visits per capita is identical in every zone in the model.

Ticket price, uniform for all zones, is a component of the travel cost to each attraction. This means we can use our regression equation to analyse how a ticket price change impacts visits per capita. Consequently, there will be a ticket price change that results in a quarter of the zones having no visits, one that results in half having no visits, and so on. This is the beginning of the construction of an aggregate demand curve that is dependent on changes in ticket price. Therefore, consumer surplus describes the area between the current ticket price (no change in price) and the ticket price change, p*, at which no visitors attend the site. This is the conceptual foundation of the algebra below.

7.2 Consumer surplus method

Following Chotikapanich and Griffiths (1998), our estimated post-regression relationship is given as:

$$\hat{y}_i = f(\widehat{\boldsymbol{\beta}}: C_i, \boldsymbol{X}).$$

Where $\hat{y}_i$ is the estimated visitors per capita for each $i \in \{1, \ldots, m\}$ zones; C_i represents the given travel cost; $\boldsymbol{X}$ is a vector of control variables; and $\widehat{\boldsymbol{\beta}}$ is a vector of estimated regression coefficients.

This estimates a relationship between visits per capita and travel cost. Importantly, it describes the estimated impact of a uniform change in travel cost across each zone, such as a change in ticket price

$$\hat{y}_i(p) = f(\widehat{\boldsymbol{\beta}}: C_i + p, \boldsymbol{X}).$$

From this, an estimate of aggregate consumer demand can be calculated (total site visitors):

$$\hat{Q}(p) = \sum_{i=1}^{m} N_i\, \hat{y}_i(p) = \sum_{i=1}^{m} N_i\, f(\widehat{\boldsymbol{\beta}}: C_i + p, \boldsymbol{X}).$$

Where N_i is the population of zone i. Consumer surplus describes the difference between current ticket price ($p = 0$) and the theoretical maximum the consumer is willing to pay, which occurs for $p*$ such that $\hat{Q}(p^*) = 0$. Aggregate consumer surplus is then estimated as:

$$\widehat{CS} = \int_{p=0}^{p=p^*} \hat{Q}(p)dp\,.$$

Specific examples for different specifications can be found in Appendix G.

This method provides the aggregate consumer surplus across all zones within the catchment of the heritage site. Two further calculations are required to achieve per capita estimates. The first is to divide the aggregate consumer surplus by the number of visitors within the catchment. The second is to multiply this figure by the percentage of visitors who travelled by car. This is due to travel cost estimates assuming travel by car. These percentages were provided by English Heritage, in the absence of bespoke figures the average percentage across available sites was used.

7.3 Per Capita Consumer Surplus

Differences in aggregate visits will generate differences in aggregate consumer surplus. Per capita estimates are initially shown to aid in the comparison between data sources. Our analysis reveals a significant consumer surplus for historic attraction sites across both sample sets. This indicates that consumers' overall willingness to pay exceeds the market price derived from ticket prices.

Table 5: Comparison in estimated consumer surplus per capita between the two sampling techniques.

Site	English Heritage (£)	Mobile Analytical (£)	Difference (£)
Audley End	2.34	4.19	1.85
Belsay Hall	4.05	4.95	0.90
Dover Castle	6.38	3.53	-2.85
Eltham Palace	3.09	4.50	1.41
Furness Abbey	7.67	3.57	-3.75
Goodrich Castle	5.50	7.49	-0.18
Mount Grace Priory	7.32	6.94	1.44
Rievaulx Abbey	6.96	6.88	-0.08
Stokesay Castle	8.47	5.77	-2.70
Whitby Abbey	17.89	6.72	-11.17
Average	5.75[5]	5.31	-0.44

The positive consumer surplus is evident in all sites, with all sites yielding a positive and significant consumer surplus underscoring the economic benefit perceived by the consumers. This represents the additional value visitors gain from historic attraction sites beyond their actual expenditure. This aligns with our understanding that the direct market value of historic attraction sites may not be best represented by purely their transactional

[5] Average excludes Whitby Abbey.

cost. These results emphasise the significant economic and cultural value historic attractions sites provide.

This comparison highlights some variability between the sampling methods. Notably, the average consumer surplus per capita is £5.75 for the English Heritage data, compared to £5.31 per capita for the mobile analytical data. However, these averages mask significant site-level differences. For example, consumer surplus per capita at Furness Abbey is £3.75 lower when estimated using mobile analytical data. In contrast, at Audley End mobile analytical data is £2.85 higher. These variations suggest that the different data collection methods are capturing distinct visitor behaviours.

There is a large difference between English Heritage sites, ranging from a consumer surplus estimate of £2.34 to £17.89. Whitby Abbey appears to be an outlier, with a significantly higher value, removing this the range would be less £2.34 to £8.47. Stokesay Castle also appears to show similar characteristics of being an outlier, though to a smaller degree. On initial look, the goodness of fit scores and skewness do not appear to explain these larger values.

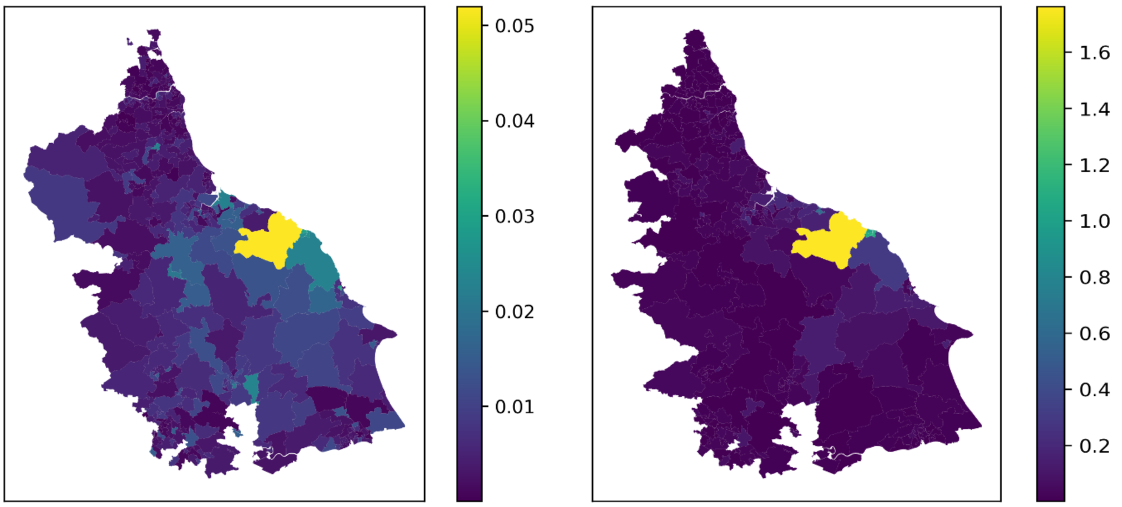

Figure 2: Density of visitors from each zone to Whitby Abbey. English Heritage (left) vs Mobile Data (right).

One explanation may come from the difference in distribution of visitors in the surrounding catchment area of Whitby Abbey, and the higher prevalence of multi-purpose visits. The English Heritage data on the left of Figure 2 shows an even spread of per capita visits throughout the catchment, including areas as far as 100 minutes away. Thus, the model creates a flatter demand curve and calculates a larger consumer surplus. The Huq data on the right, not only has significantly more aggregate visits, but they are also concentrated more closely to the site. This stark difference in distribution between the two data sources for Whitby Abbey could be the cause of such a large difference in consumer surplus per capita estimates. To foretell some of the conclusions from Section 8.3, there appears to be greater variability to changes in the catchment area between Whitby Abbey and Stokesay Castle for both sampling methods, indicating a misspecification here perhaps due to the presence of multi-purpose visits. With the removal of these two sites, the correlation increases to 0.7.[6]

Mobile analytical data provides more consistent values, ranging from £3.53 to £7.49. The lowest of these was observed for Furness Abbey, which had inconsistencies within the data especially in the case of the linear models, which predicted insignificant consumer surplus values.

7.4 Aggregate Value

Differences in estimated aggregate visitor numbers will result in differences in aggregate measures of consumer surplus. Nevertheless, values utilised in the social cost-benefit analysis will need to be aggregated. Table 6 displays aggregate consumer surplus and a breakdown of the other economic values that can be attributed to each site. The summation of all these values is what we are calling “recreational value”. It includes consumer surplus but also incorporates other cost elements, such as ticket revenue, travel costs, and opportunity costs. This represents the breakdown of values that could be used in net present value calculations.

We observe significant differences between the Consumer Surplus and Total Recreational value between English Heritage and the mobile analytical data, primarily due to the visitor footfall numbers. This difference in footfall numbers also translates to differences in Recreational Value, primarily attributed to the reduction/addition of ticket revenue from visitors.

Table 6 breaks down market costs and how these compare to the non-market value gained by consuming that good (the consumer surplus). In the absence of this non-market value, and in the context of government decision making, the cultural asset may be undervalued. Therefore, the consumer surplus numbers represent the additional value that the consumer gains from the heritage site experience.

6 Further justification is provided as to why these sites are anomalies in section 8.3; however, the removal of this and the low number of sites should be treated with caution.

Table 6: Aggregate consumer surplus (CS) and recreational value.

Site	Metric	EH Value	Huq Value
Audley End	Consumer Surplus	£517,325	£266,557
Audley End	CS Per Capita	£2.34	£4.19
Audley End	Ticket Revenue	£4,522,954	£1,419,846
Audley End	Travel Cost	£845,029	£263,107
Audley End	Total Opportunity Cost	£1,042,333	£317,740
Audley End	Total Recreational Value	£6,927,641	£2,267,250
Belsay Hall	Consumer Surplus	£235,579	£199,126
Belsay Hall	CS Per Capita	£4.05	£4.95
Belsay Hall	Ticket Revenue	£870,945	£719,129
Belsay Hall	Travel Cost	£192,886	£128,195
Belsay Hall	Total Opportunity Cost	£256,562	£169,806
Belsay Hall	Total Recreational Value	£1,555,973	£1,216,256
Eltham Palace	Consumer Surplus	£259,823	£147,326
Eltham Palace	CS Per Capita	£3.09	£4.50
Eltham Palace	Ticket Revenue	£2,257,839	£890,557
Eltham Palace	Travel Cost	£159,290	£80,790
Eltham Palace	Total Opportunity Cost	£273,712	£124,188
Eltham Palace	Total Recreational Value	£2,950,663	£1,242,861
Mount Grace Priory	Consumer Surplus	£123,932	£47,980
Mount Grace Priory	CS Per Capita	£5.28	£6.94
Mount Grace Priory	Ticket Revenue	£402,007	£122,032
Mount Grace Priory	Travel Cost	£125,471	£40,949
Mount Grace Priory	Total Opportunity Cost	£123,666	£38,702
Mount Grace Priory	Total Recreational Value	£775,076	£249,663
Stokesay Castle	Consumer Surplus	£82,147	£8,515
Stokesay Castle	CS Per Capita	£8.47	£5.77
Stokesay Castle	Ticket Revenue	£280,243	£24,048
Stokesay Castle	Travel Cost	£65,370	£6,998
Stokesay Castle	Total Opportunity Cost	£80,333	£8,604
Stokesay Castle	Total Recreational Value	£508,093	£48,165

To display this further, Table 7 shows the consumer surplus per capita as a percentage of the ticket price. Our consumer surplus is the value above the cost, including travel, time and ticket. This table is intended to show the scale to which consumers gain additional value above the entrance price. On average, the consumer surplus is between 45%-58% of the ticket price, depending on the data source used. This means that 45% to 58% of the value visitors derive from their experience exceeds the market price, representing the non-market benefits of the heritage site. These benefits align with the Culture and Heritage Capital programme's goal to capture a more comprehensive picture of the economic value of culture and heritage assets.

Table 7: Consumer surplus per capita as a percentage of ticket price

Site	Ticket Price (£)	EH	Huq
Audley End	17.90	13.07%	23.35%
Belsay Hall	12.38	32.71%	39.98%
Eltham Palace	16.04	19.26%	28.05%
Furness Abbey	8.33	87.88%	42.86%
Stokesay Castle	10.22	82.88%	56.46%
Dover Castle	22.40	36.05%	28.47%
Goodrich Castle	10.47	73.26%	71.54%
Mount Grace Priory	11.48	45.99%	60.45%
Rievaulx Abbey	12.66	37.91%	54.34%
Whitby Abbey	12.56	142.44%	53.50%
Average	13.44	57.15%	45.90%

7.5 Alternative technique for mobile analytical data

The structure of the mobile data, where the distribution across the four 4-digit postcodes must total 100%, introduced a higher degree of skewness that was not necessarily reflective of actual travel behaviour or distance impacts. Instead, this skewness was an artefact of the data structure itself. As a result, areas with fewer zones tended to disproportionately attribute more visitors to postcodes with higher percentages, typically those closer to the site.

To address this, we expand the use of data from April 2020 to March 2023[7] under the assumption that the visitor profile and their relationship to the site remains constant over time.[8] Therefore, assuming the reasons people visit the site have not changed, we can estimate using the larger sample size, and thereby more accurate measurements of where visitors travelled from.[9]

Table 8: Changes in the magnitude difference between the models, with the log-log being the reference case.

Site	Linear (2020)	Linear (2023)	Log-Linear (2020)	Log-Linear (2023)	Log-Log (2020)	Log-Log (2023)	Linear -Log (2020)	Linear -Log (2023)
Audley End	29.32	7.2	1.1	1.11	1	1	N/A	18.35
Belsay Hall	2.38	1.62	1.08	1.11	1	1	2.7	1.83
Dover Castle	200.55	3.36	1.1	1.12	1	1	3136.82	6.44
Eltham Palace	1.63	1.25	1.1	1.1	1	1	1.78	1.32
Furness Abbey	17.45	-	1.09	-	1	1	27.83	-
Goodrich Castle	7.32	3.46	1.33	1.34	1	1	11.22	4.06
Mount Grace Priory	2.83	2.31	1.25	1.24	1	1	2.84	2.3
Rievaulx Abbey	10.45	5.11	1.23	1.18	1	1	9.03	5.38
Stokesay Castle	5.12	4.04	1.19	1.22	1	1	16.73	8.63
Whitby Abbey	5.26	4.76	1.26	1.25	1	1	5.77	5.52
Average	9.89	3.68	1.16	1.19	1	1	400.44	5.98

7 It should be noted this covers a period to which the UK was in lockdown. This should be accounted for in the data, and as we present per capita rates should not be an issue.

8 The period of lockdown may have affected people attitudes to travel – however we do not observe this within the English Heritage data. Preferably, we would utilise a later period however due to data constraints at this time are unable to. Future research can utilise a period not as directly impacted by Covid-19.

9 Jones et al. (2020), found that with the addition of world heritage site status that demand, and consumer surplus, did not fluctuate significantly for Mount Fuji.

We see the differences between the linear dependent variables and non-linear dependent variables converging, suggesting the sample is becoming more efficient in all our models. This is quite pronounced, with the average difference between the linear model moving between 9.89x (excluding Dover Castle) and that of the log-log model, to an average of 3.68x – in the latter calculations we also do not have to remove the large anomalies, so the difference is even larger. The predominant effect of this is an increase in models with a linear dependent variable, but also a decrease in the log-log variable itself.

This significance convergence would suggest that with additional years of data, the differences between the models would be like that of the English Heritage sample.

In all cases, we see a decrease in the estimated value. This overarching trend, alongside the significant reduction in differences between the dependent linear variable and log dependent variable, would suggest this is a result of a decrease in the level of skewness in the data as opposed to a change in consumer demand.

This also improves the relationship of our variables between the EH and Huq data, where we now find a positive correlation of 0.52. The removal of Stokesay Castle and Whitby Abbey, which appear to be significant outliers in the English Heritage data, brings this positive correlation up to 0.72.

Table 9: Absolute difference between the consumer surplus per capita figures.

Site	Huq (£)	Huq 3 Years (£)	Difference (£)
Audley End	4.19	3.52	-0.67
Belsay Hall	4.95	4.22	-0.73
Dover Castle	3.53	3.52	-0.01
Eltham Palace	4.50	4.23	-0.27
Furness Abbey	3.57	3.38	-0.19
Goodrich Castle	7.49	7.02	-0.47
Mount Grace Priory	6.94	6.24	-0.70
Rievaulx Abbey	6.88	6.18	-0.80
Stokesay Castle	5.77	4.98	-0.79
Whitby Abbey	6.72	5.24	-1.48

8 Robustness

8.1 Addressing English Heritage visitor data anomalies

In the previous models, all datasets were utilised in their original form. Given the size of the datasets for each English Heritage site as well as the mobile analytical dataset, we assumed that this data was as true to real life as possible. However, it became apparent that there were anomalies in the data, specifically in postcodes especially close to the heritage site. To address these anomalies, data was excluded if either to these two conditions were met:

1. The total number of visitors was equal to or more the 0.5 of the population.
2. Audley End had the highest amounts of removed data, reducing the total number of data points from 1586 to 1582, Belsay Hall, Dover Castle and Eltham Palace had 1 data point removed.
3. The site with the highest visitors-to-population ratio has at least five times the ratio of the second highest site.

The results per capita are shared for the four model types below:

Table 10: Comparison of consumer surplus per capita estimates for data with anomalies removed.

Site	English Heritage (£)	Anomalies removed (£)	Difference (£)
Audley End	2.34	3.14	0.80
Belsay Hall	4.05	4.25	0.20
Dover Castle	6.38	5.99	-0.39
Eltham Palace	3.09	3.37	0.28

8.2 Sensitivity to polygon changes

Table 1 provided the visitor numbers predicted by the mobile analytical company. We observed discrepancies between these estimates and those provided by English Heritage. Upon further consultation with the mobile analytical company, we received revised visitor numbers, which are presented in Table 11. These revisions come from adjusting the underlying polygons.

The changes made to the polygons were:[10]

- Inclusion or exclusion of car park areas
- Inclusion or exclusion of pathways from car parks to sites
- Extension of areas further into the gardens

Table 11: Changes in aggregate visitor numbers from updated polygons (000s).

Site	Initial Huq (2020/21)	Revised Huq (2020/21)	Initial Huq (2021/22)	Revised Huq (2021/22)	Initial Huq (2022/23)	Revised Huq (2022/23)
Audley End House and Gardens	45	45	143	143	95	95
Beeston Castle	24	59	28	76	25	44
Belsay Castle	40	40	44	44	60	60
Bolsover Castle	23	46	54	95	57	92
Brodsworth Hall	17	47	27	52	43	51
Dover Castle	92	92	171	171	267	267
Eltham Palace	38	38	109	109	147	147
Farleigh Castle	5	5	22	22	27	27
Furness Abbey	19	19	15	15	44	44
Goodrich Castle	22	22	44	44	38	38

10 Polygons are shared in Appendix E.

Site	Initial Huq (2020/21)	Revised Huq (2020/21)	Initial Huq (2021/22)	Revised Huq (2021/22)	Initial Huq (2022/23)	Revised Huq (2022/23)
Kenilworth Castle	48	48	104	104	74	74
Mount Grace Priory	10	21	49	65	31	42
Rievaulx Abbey	7	35	34	82	31	75
Stokesay Castle	2	3	9	13	29	29
Whitby Abbey[11]	173	125	324	236	374	233

We observed varying degrees of correlation between the English Heritage data and the mobile analytical data across different time periods.

Table 12: Correlation between English Heritage and mobile data.

Period	Original Data Correlation	Revised Data Correlation
2020/21	0.53	0.66
2021/22	0.82	0.87
2022/23	0.81	0.9

Notably, the differences during the 2020/21 period, which is the focus of our analysis, were somewhat larger compared to the following years. This discrepancy posed a challenge because the 2020/21 period coincided with mandatory online bookings for English Heritage sites, which would provide the most accurate data on visitor origins. We decided to utilise the data from when English Heritage required online bookings, as it provides the most representative sample. This approach also allows us to assess the effectiveness of raw mobile data without post-hoc adjustments.

For the initial mobile analytics data, the polygons were defined through desk-based research utilising Google Maps and images from internet sources such as the English

11 Very large differences are observed in the visitor counts for Whitby Abbey, this is linked to a relatively significant change in boundaries. In our analysis, we choose to use the original boundaries and then explore the impacts in the robustness section (section 8).

Heritage website. Practically, this task could be outsourced to specific heritage sites; however, this will not be possible in all scenarios.

When using three years of data, we have the following changes:

Table 13: Adjustments using the 3 years of mobile analytical data between the changes in the polygons.

Site	Old (£)	New (£)	Difference (£)
Mount Grace Priory	6.25	6.01	-0.24
Rievaulx Abbey	6.18	6.08	-0.10
Stokesay Castle	4.98	4.60	-0.38
Whitby Abbey	5.02	5.24	0.22

The changes to per capita rates using this remained relatively small, and with no clear direction found. This would result in a larger difference if we were to interpret the results based on the changes to number of visitors, which is shown in Section 8.2 to be more pronounced.

Table 14: Changes in magnitude differences between the old and new polygons, using 3 years of mobile analytical data.

Site	Linear (Old)	Linear (New)	Log-Linear (Old)	Log-Linear (New)	Log-Log (Old)	Log-Log (New)	Linear-Log (Old)	Linear-Log (New)
Mount Grace Priory	2.31	2.18	1.24	1.23	1	1	2.3	2.17
Rievaulx Abbey	5.11	5.39	1.23	1.19	1	1	5.38	5.26
Stokesay Castle	4.04	3.23	1.22	1.2	1	1	8.63	5.99
Whitby Abbey	4.76	4.36	1.25	1.25	1	1	5.52	4.89
Average	4.055	3.79	1.235	1.2175	1	1	5.4575	4.5775

Table 14 indicates that redefining polygons might improve differences between models. However, more case studies are required. One explanation is that these sites after being redefined picked up more visitors, thus increasing the granularity and number of data points. This could lead to a lower level of skewness in the data in a similar way that increasing the number of years does. Appendix E shows the changes to polygons.

Despite these adjustments, we chose not to utilise the newly provided polygons for the following reasons:

1. The primary objective of this study was to assess the practicality and ease of use of mobile analytical data. By adhering to our initially defined polygons rather than the revised ones, we aimed to evaluate the usability and accuracy of mobile data as originally provided. This approach allows us to identify potential usability challenges that end users might face.
2. Adjusting polygons based on expected visitor numbers would also not always be possible in real-world applications. The ability to make such adjustments requires specific knowledge that wouldn't be available. By relying on the initial data, we allow for a more realistic scenario where you may not have the opportunity to refine the data post hoc.
3. This approach has also allowed us to maintain a consistent methodology throughout this report. During the study, many challenges were faced, and solutions were considered. Pursuing the exact visitor numbers, while important, would have detracted from the main objective of understanding the per capita ratio, making it an unrealistic use of resources.
4. Lastly, this methodology provided a critical opportunity to evaluate the quality of the data as initially supplied. It allowed us to identify and document any inherent limitations or inaccuracies in the mobile analytical data, whether human-related or data-related, offering valuable insights for future data refinement and methodological improvements.

8.3 Changes in catchment areas

The travel cost model assumes that the primary motivation for a visitor's trip is the site itself. This assumption simplifies the analysis but can introduce biases if visitors have multiple purposes for their trip. For example, a visitor travelling 100 minutes to visit a site may also be visiting other attractions, friends, or business engagements in the area. Consequently, the entire travel cost should not be attributed solely to the site visit. This lack of detailed trip purpose data limits the accuracy of our consumer surplus estimates. Currently, the decision to choose 100 minutes was chosen to best evaluate the data by ensuring a range of data scales could be considered.

The impacts are consequential:

1. With our current approach, we include an estimate for travel costs including fuel and time. Decreasing this would potentially eliminate issues of overinflating these costs due to multipurpose visits being more likely from distances that our further away.
2. However, we would risk underrepresenting the broader economic impacts of the site by having a too-tight definition that excluded visitors.

The ideal catchment area is likely to not be homogenous between sites, as identified sites such as Whitby Abbey, which appear to not have a significant population surrounding the site, are identified as having a higher consumer surplus. This could be an impact of the catchment area being defined as too small.

Table 15: Consumer surplus estimates per capita for the log-log model with varying catchment areas using English Heritage data.

Site	40 Min	60 Min	80 Min	100 Min	120 Min
Audley End	£2.50	£2.14	£2.25	£2.34	£2.57
Belsay Hall	£7.18	£4.26	£3.78	£4.05	£4.62
Eltham Palace	£1.53	£2.31	£2.88	£3.09	£3.20
Mount Grace Priory	£3.79	£4.37	£5.19	£5.50	£5.83
Stokesay Castle	£3.83	£5.96	£6.61	£8.47	£10.89
Whitby Abbey[12]	£5.02	£11.44	£14.23	£17.89	£51.48

Table 16: Consumer surplus estimates per capita for the log-log model with varying catchment areas using mobile analytical data.[13]

Site	40 Min	60 Min	80 Min	100 Min	120 Min
Audley End	£1.59	£2.00	£2.85	£3.52	£4.39
Belsay hall	£2.82	£3.25	£4.20	£4.22	£5.41
Eltham Palace	£2.46	£3.58	£4.21	£4.23	£4.25
Mount Grace Priory	£4.62	£3.93	£5.09	£6.01	£6.81
Stokesay Castle	£1.63	£2.37	£2.99	£4.60	£6.73
Whitby Abbey	£2.47	£3.68	£5.09	£5.24	£9.00

Considering just the Log-Log model, Tables 15 and 16 display the consumer surplus per capita across five different catchment sizes. Audley End and Belsay Hall in the English

12 Whitby Abbey is included in this table due to it being an anomaly.
13 In this example, we use the updated polygons for Audley End and Stokesay Castle discussed in section 8.2.

Heritage data appear to be consistent across catchment size, but across both the English Heritage and the 3-year Huq data there is a relative trend of increasing catchment size increasing consumer surplus per capita estimates.

This is not unexpected, as increasing the catchment size increases the maximum travel cost for which visitors are willing to attend the site, thus increasing consumer surplus estimates. This assumes visitors are traveling solely for the site, which may not always be the case, particularly for those traveling from long distances who may have other purposes for their trip. If such visitors are included, the model will wrongly include them in consumer surplus estimates. It is therefore clear that each site will have a catchment size unique to them, whereby you can assume that visitors within this catchment are solely visiting the historic site.

For example, consider Stokesay Castle, which shows a significant increase in consumer surplus per capita as the catchment size expands in both the English Heritage and mobile analytical samples. Located in a rural area with a low surrounding population, the site has 282 MSOAs within a 100- to 120-minute drive. Of these 282, there are 82 with a visitor rate per capita above the median level for the sample. By including these visitors, the model assumes that there are many visitors with a high travel cost attending the site and this may be why we see such a jump in consumer surplus per capita estimates when moving into the 100- and 120-minute catchments. This is accurate, so long as these visitors are not attending the local area for ulterior reasons and therefore highlights the need for individual specification of catchment for each site.

The strong relationship observed between the two anomalous sites, Stokesay Castle and Whitby Abbey, in terms of their catchment areas, is a promising finding. It suggests that the differences in the main findings are more akin to a specification issue as opposed to a divergence between the sampling method. Historic England plans to conduct qualitative research to better understand the relationship between distance to a site and the likelihood of a visit being the primary purpose of a trip or part of a multi-purpose trip, aiming to improve the assumptions used in our models.

8.4 Market vs non-market costs

We explored separating the travel cost variable into its market and non-market components. This meant creating two variables, one for the travel expenses and ticket cost (market) and another for the opportunity cost of the consumers time (non-market). The idea was to estimate the consumer surplus of the time spend travelling, to obtain a purely non-market value of the time consumers gain in surplus by travelling to each heritage site. However, the collinearity between the variables for travel cost and for opportunity cost created misspecification in our model, generating unrealistic coefficient values, high standard errors, and unreliable consumer surplus estimates.

For example, Table 17 and Table 18 display the variance inflation factor scores for Audley End and Belsay Hall. You can see evidence of strong collinearity between travel cost and opportunity cost, suggesting misspecification in this modelling structure.

Table 17: Variance Inflation Factor (VIF) Scores for Audley End.

Variable	VIF
Op Cost	70.3111366
Travel Cost	423.1020806
Income (ln)	190.9234280

Table 18: Variance Inflation Factor (VIF) Scores for Belsay Hall.

Variable	VIF
Op Cost	274.2313459
Travel Cost	1381.6962430
Income (ln)	469.8148782

8.5 Model specification

We tested different model specifications to compare regression results. These included two OLS specifications: one where the dependent and travel cost variables were square-rooted, and another where their inverse was applied. We also ran a Generalized Linear Model (GLM) with gamma-distributed errors and a log-link function.

For the English Heritage sample, the square root models there was a large degree of heterogeneity between the log-log models, based on metrics such as R-squared and AIC scores. On average, the difference between the R squared values was 0.01, however, this masks large differences observed, for example Dover Castle saw a 0.13 increase in R squared value compared for the square root model, whereas Eltham Palace saw a 0.16 increase when using the log-log model over the square root model.

For the mobile analytical data, the log-log model performs demonstrably better. We see across all sites an improved R squared value, with the average difference in Adj. R squared is 0.11. The difference decreases to 0.06 when using 3 years of data, suggesting this is driven largely by the skewness observed in the main findings.

We find that the square root transformation may not fully capture the non-linear relationship between travel cost and visitation in the mobile analytical data. Given the easier interpretation of the log-log model, the non-conclusive results from the English Heritage sample and the preferred results for the mobile analytical data it suggests that the log-log model still performs most suitably, however, when expanding this to more sites, this should be re-checked.

The inverse model performs worse across all sites and data sampling in terms of significance of the variables, alongside goodness of fit scores. The theoretical consideration of such model would be that the impact of increased travel cost diminishes as costs increase. Given the poor performance of this model, this does not seem to be the case. This could indicate that our current catchment areas is restrictive enough, as a diminishing effect of an increase in travel costs might be expected as individuals travel for more than the sole reason of visiting the site.

The GLM with a gamma distribution and log-link function produced coefficients very similar to the log-log model. This is expected, as both models assume a multiplicative relationship between the variables, and the log-link function in the GLM models the log of the expected value of the dependent variable. However, there was no clear indication that the gamma distribution provided a significantly better fit for the distribution of the residuals. In some cases, we observed both higher and lower t-values, but no consistent trend emerged. The significance of the distance variable remained high across all models, aligning with the robust economic theory that as distance increases, visitation decreases.

9 Discussion

9.1 Mobile analytical approach

This study demonstrates the potential to estimate consumer surplus using mobile analytical data. While initial models revealed differences between estimates derived from English Heritage data and mobile analytical data, expanding the scope of the time frame reduced the differences observed. All studies showed a moderate positive correlation across the observed sites, although further research is needed to determine the significance of these correlations.

Currently, we cannot conclusively determine which of the two data sources is more accurate. Initially, we expected the English Heritage data, based on an online booking system, to be the most accurate. However, data anomalies and greater heterogeneity in results were observed using this data. Whether these differences reflect variations in site characteristics or underlying data issues remains unclear.

Despite these issues, both data techniques offer significant improvements compared to traditional survey methods and help eliminate common survey biases:

1. A significantly higher sample size is observed in both datasets. For English Heritage, for the specific time observed it represents nearly all visitors to the site. For later years, this would decrease but still be high in comparison to a survey. It is unclear the exact sample size of the mobile analytical, however, given the scope of information provided it reflects a significant sample size.
2. Seasonal differences are accounted for fully within both these sample methods as opposed to surveys, which will represent a snapshot in time.
3. Self-selection biases may be reduced, people who are more likely to answer surveys may have certain observable and unobservable characteristics. During the period we observed with English Heritage, all visitors were required to book online. In the case of mobile data, there could still be some self-selection with the choice of apps.
4. The use of mobile analytical data can be used to look at a period in the past, whereas a survey can only be used to look at one present point of time.
5. Mobile analytical data collection is significantly cheaper than conducting large-scale surveys.

There are positives that can be observed from survey methods, the predominant one being the ability to better observe repeat visitation at an individual level, and the ability to ask about the purpose for the visit. The former allows individual travel cost methods, using Poisson regression models, to be used. This may be possible with certain mobile analytical companies, although anonymisation of data means that the individuals characteristics will still need to be homogenous at their spatial level, as opposed to individual heterogenous data.

The sole purpose visit remains more difficult, and it is where qualitative data might be suitable to be collected alongside this. This does not necessarily need to be done for all sites, but a range of sites with different characteristics would want to be evaluated. Much of this data might already be collected by visitor sites.

Our study used a 100-minute sole-purpose catchment, this was chosen to balance the need to evaluate the technique, with the main goal of establishing whether the data was accurate enough to use this methodology. One alternative to this, not explored in this study, is to utilise Smith and Kopp (1980) approach, which uses an altered error correction model to detect the point where residuals exhibit progressively more pronounced non-random fluctuations, which could be used to establish a dynamic point per site that distance stops significantly explaining the reason for the trip.

For these reasons, it is certain that a significant degree of uncertainty exists in all current methodologies to observe consumer surplus through travel cost methods. Therefore, we recommend that more research needs to be conducted to consider a wider role out of this type of mobile analytical data across heritage sites, and potentially across more cultural sites in relation to the CHC programme. We however do remain hopeful that this is a methodology that can represent a significant improvement in the current methods used.

9.2 Broader context of cultural heritage valuation

While this study's primary focus was on the use of mobile analytical data to estimate consumer surplus for historic attraction sites, it is important to understand the findings within the broader context of cultural heritage valuation. The valuation of cultural heritage, particularly its non-market aspects, is still in its infancy. Accurately attributing non-market value to cultural heritage assets remains a significant challenge and is like the issues faced in the field of natural capital.

As Navrud and Ready (2002) explain, cultural heritage goods are often public goods, characterised by non-rivalry and non-excludability. One person’s enjoyment of a heritage site does not diminish the experience for others, and it is difficult to prevent people from benefiting from these sites. Consequently, the full social value of these goods is often not reflected in market transactions, potentially leading to market failure.

A consequence of this market failure is deadweight loss. In the case of cultural heritage sites, this can occur when entrance fees are set below market rates to ensure access or when access is restricted to preserve the site. This often happens because many heritage sites operate as non-profit entities and aim to balance conservation with accessibility. Additionally, public subsidies are frequently used to support these sites, which can further contribute to inefficiencies. While this supports equity, it introduces inefficiencies that shift costs onto the public sector (via subsidies) or the private sector (via lost revenue). Quantifying these inefficiencies could help clarify their distribution and guide policies to minimise welfare losses while maintaining accessibility

Despite these inefficiencies, cultural heritage assets generate significant positive externalities that can possibly offset the deadweight loss. Throsby (2019) discusses how cultural heritage produces non-market value by fostering social cohesion, educational benefits, and enhancing community well-being. These benefits extend beyond the immediate users of the site to the wider society. These positive externalities, not always captured in regular market transactions, if greater than the deadweight loss could result in a less-than-optimal public welfare decision. Therefore, methods to capture the additional value are essential for Social Cost Benefit Analysis.

Future research could explore the dynamic between market-generated value, represented by ticket prices, and non-market cultural value, building upon Throsby's (2019) framework. In the travel cost method, the combination of travel cost, travel time, and ticket price raised concerns about theoretical consistency, particularly the treatment of consumer surplus as a proxy for cultural value. Attempts to separate these components resulted in high levels of multicollinearity, indicating that a different approach may be required. Addressing this issue could provide greater clarity on how inefficiencies, such as deadweight loss, arise in cultural heritage contexts.

Furthermore, while the travel cost method captures willingness to pay, it does not explain why valuations differ between market and non-market contexts. Future research could adopt methodologies like those used by Krekel et al. (2019) and Tubadji (2023) to compare marginal utilities across market-clearing and non-market settings. This would provide a more robust understanding of how individual preferences interact with systemic inefficiencies. Both approaches could contribute to better-informed strategies for maximising welfare gains.

This mirrors challenges seen in the field of natural capital, where non-market values are difficult to attribute to the capital itself and are instead reflected in the ecosystem services—the tangible and intangible benefits provided. Therefore, the evolution of methodologies must go hand in hand with a clearer taxonomy and theoretical framework defining cultural capital. Without this parallel work, the field risks falling further behind other areas of environmental and economic valuation. Advancing both the tools to measure non-market value and the conceptual understanding of cultural capital is essential for ensuring that the value of cultural heritage assets is fully recognised and integrated into broader economic and policy discussions.

The Arts and Humanities Research Council (AHRC) has initiated numerous projects aimed at addressing both the methodological and theoretical gaps in cultural heritage valuation. Additionally, ongoing research by the Department for Digital, Culture, Media and Sport (DCMS) and its Arms-Length Bodies—such as Historic England and Arts Council England—continues to provide new evidence and develop improved methodologies to support the wider Cultural Heritage Capital Programme. These efforts will be significant in advancing the field and ensuring that cultural heritage is given its due place in economic evaluations and policy frameworks.

10 Social Cost-benefit Analysis

This section provides a demonstration of an investment decision analysis for historic attraction sites across four scenarios, using a 3% discount rate over a 10-year period, following HM Treasury Green Book guidance. This analysis will include both admission fees as the primary benefit, and consumer surplus (CS) where applicable. For illustrative purposes, the values are derived from Belsay Hall, but they should not be treated as accurate estimates or representations of real-life interventions.

10.1 Key parameters:

- Consumer Surplus Per Capita: Calculated at £4.95 using the Travel Cost Method outlined in this report.
- Average Admission Fee: £12.38.
- Annual Visitors: 58,000.

10.2 Key concepts:

$$\text{Discounted Market Benefits} = \sum(visitors * admission\ fee * DF)$$

Discounted Benefits are the present and future market benefits. In this scenario, this is cash flow deriving from site-specific ticket sales. Other cash flows are likely to also exist but are not considered in this simplified demonstration.

$$\text{Discounted Recreational Value} = \sum(visitors * admission\ fee * \ Consumer\ Surplus\ Per\ Capita * DF)$$

Discounted Recreational Value are the present and future market and calculated non-market benefits (in this example, the estimated consumer surplus). This is not the same “recreational” value that is cited earlier in the document, as it does not include values deriving from travel expenses and opportunity cost of time.

$$\text{Discounted Costs} = \sum(Annual\ Costs * DF)$$

Discounted costs are the present and future costs over a given time sample, multiplied by the discount factor.

$$Profitability\ Index\ (PI) = \frac{Discounted\ Market\ Benefits}{Discounted\ Costs}$$

Profitability Index is a standardised measure that considers the future discounted cash flows against the future discounted costs.

$$Recreational\ Value\ Index\ (RVI) = \frac{Discounted\ Recreational\ Benefits}{Discounted\ Costs}$$

Recreational Value Index (RVI) is a measure designed to illustrate the impact of including the consumer surplus in the profitability index, considering future discounted benefits against the future discounted costs.

Table 19 presents four distinct scenarios designed to illustrate the financial and economic implications of different investment and operational decisions for a historic attraction site when using the consumer surplus values from this study. These scenarios are compared against a baseline counterfactual scenario, which assumes no additional investments or changes beyond the site's current operation. This counterfactual serves as a benchmark to assess the additionality of each intervention, following the principles outlined in HM Treasury's Green Book. These scenarios aim to demonstrate that in the absence of non-market estimates, the undervaluation of heritage sites may lead to suboptimal investment.

- **Scenario 1 (Baseline):** Without consumer surplus, the profitability index (PI) is below 1, necessitating subsidies to cover operational costs. Including consumer surplus shows a positive net present value (NPV) of £1,749,886, indicating the site's non-market value.
- **Scenario 2 (Repair Costs):** The introduction of repair costs leads to a negative NPV without consumer surplus, underscoring financial risk. However, including consumer surplus results in an NPV of £744,996 and an RVI of 1.1, suggesting continued investment is justified.
- **Scenario 3 (£2.5M Investment + Repair):** A significant investment boosts visitor numbers, however the repair costs (same as scenario 2) in total leads to a negative NPV without considering consumer surplus. Including the uplift from CS results in a positive NPV of £2,012,498 and an RVI of 1.20, making a compelling case for investment. Scenario 3 including consumer surplus uplifts proposes that the CS may increase because of the investment, increasing the RVI to 1.31.

- **Scenario 4 (£2.5M Investment):** This scenario examines the effects of targeted investment and the potential for increased consumer surplus. The benefit-cost ratio (BCR) exceeds 1, affirming the investment's viability without the inclusion of consumer surplus. Including the consumer surplus raises the BCR to 1.59, indicating a robust investment opportunity. Scenario 4 also includes a consumer surplus uplift due to the investment, thus bringing the BCR to 2.18.

Table 19: Scenario analysis for example social cost benefit calculation.

Parameter	Scenario 1: Baseline	Scenario 2: Repair Costs	Scenario 3: £3M Investment	Scenario 3: (Increased CS)	Scenario 4: £2.5M Investment	Scenario 4: (Increased CS)
Visitors	£58,000	£58,000	£81,000	£81,000	£81,000	£81,000
Admission Fee (£)	£12.38	£12.38	£12.38	£12.38	£12.38	£12.38
Consumer Surplus (£/capita)	£4.95	£4.95	£4.95	£6.50	£4.95	£6.50
Annual Operating Costs (£)	£800,000	£704,000	£704,000	£704,000	N/A	N/A
Total Repair and Maintenance Costs (10 Yrs) (£)	N/A	£2,138,038	£2,138,038	£2,138,038	N/A	N/A
Total Investment to improve site (£)	N/A	N/A	£2,500,000	£2,500,000	£2,500,000	£2,500,000
Market Discounted Benefits (£)	£6,125,027	£6,125,027	£8,553,916	£8,553,916	£2,428,890	£4,655,553
Consumer Surplus (Non-market benefits) (£)	£2,499,021	£2,499,021	£3,420,184	£4,491,152	£971,163	£2,226,663
Discounted Costs (Operating, Repair & Investment) (£)	£6,824,162	£7,829,053	£9,961,603	£9,961,603	£2,132,550	£2,132,550

Parameter	Scenario 1: Baseline	Scenario 2: Repair Costs	Scenario 3: £3M Investment	Scenario 3: (Increased CS)	Scenario 4: £2.5M Investment	Scenario 4: (Increased CS)
Net Present Value (NPV) Without CS (£)	-£699,135	-£1,704,026	-£1,407,686	-£1,402,424	N/A	N/A
Net Present Value (NPV) With CS (£)	£1,749,886	£744,996	£2,012,498	£3,084,465	N/A	N/A
Profitability Index (PI)	0.9	0.78	0.86	0.86	N/A	N/A
Recreational Value Index (RVI)	1.26	1.1	1.2	1.31	N/A	N/A
Benefit Cost Ratio (BCR) Without CS	N/A	N/A	N/A	N/A	1.13	1.59
Benefit Cost Ratio (BCR) With CS	N/A	N/A	N/A	N/A	1.59	2.18

These scenarios serve as demonstrations of how counterfactual analysis can be used to build a business case. In scenarios 1 to 3, the inclusion of non-market values such as consumer surplus highlights the wider benefits not accounted for by market value alone. This demonstrates the potential to justify grant aid or subsidies to support the site. Scenario 4 demonstrates a simplified, but more classical approach to Benefit-Cost Ratio (BCR) analysis, where the direct impact of the investment is evaluated.

By comparing the baseline to alternative scenarios, decision-makers can determine the extent to which interventions generate additional benefits. This counterfactual approach ensures alignment with Green Book guidance by emphasising additionality and providing justification for investments. These examples are not full cost-benefit analyses and do not account for all factors such as the direct impact of the investment, multiplier effects, and additionality. The full calculations and economic analysis are presented in Appendix F.

11 Conclusions

This study explored the use of mobile analytical data to estimate consumer surplus for heritage sites, comparing it with English Heritage data. While discrepancies and heterogeneities were observed between the two data sources, the study demonstrated the feasibility and potential advantages of using mobile data, including higher sample sizes, reduced biases, and cost efficiency over traditional survey techniques.

The findings highlight the need for further research to validate the accuracy and reliability of mobile analytical data in different contexts. Despite some challenges, such as violations of the sole purpose of visit assumption, worries over visitor estimates and sensitivity to polygon changes, and limitations in tracking individual repeat visits, mobile data offers a promising alternative to traditional survey methods.

We recommend integrating mobile analytical data into broader heritage site valuation methodologies and conducting additional studies to refine this approach. Historic England will continue this research expanding on the number of sites, alongside conducting qualitative research. This integration can support more accurate economic assessments, informing better management and conservation strategies for heritage sites.

Overall, this study contributes to the ongoing efforts to enhance the valuation of cultural heritage capital, paving the way for a more effective way of articulating the value of cultural and heritage.

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13 Appendices

13.1 Appendix A

The goodness of fit scores is provided for the five main models that we utilise in our analysis. We provide results for the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), adjusted R squared (Adj. R Sq.) and skewness. This shows that the performance of the log-log model consistently performs well and supports our analysis in the main text that the log-log model is the most suitable. Further goodness of fits of scores can be provided on request.

Table A1: Comparison of statistical models across various sites for English Heritage data.

Site	Metric	Linear	Log-Linear	Linear-Log	Log-Log
Audley End	AIC	-2274.82	4016.99	-2317.65	3972.52
Audley End	BIC	-2259.42	4032.38	-2302.25	3987.91
Audley End	Adj. R Sq.	0.087	0.47	0.12	0.49
Audley End	Skewness	23.28	-0.44	23.14	-0.46
Belsay Hall	AIC	-812.47	746.74	-820.42	741.70
Belsay Hall	BIC	-801.99	757.22	-809.94	752.18
Belsay Hall	Adj. R Sq.	0.23	0.52	0.26	0.53
Belsay Hall	Skewness	6.38	-0.64	6.26	-0.73
Eltham Palace	AIC	-4958.77	3980.43	-4993.34	3915.93
Eltham Palace	BIC	-4943.35	3995.85	-4977.92	3931.35
Eltham Palace	Adj. R Sq.	0.083	0.44	0.11	0.47
Eltham Palace	Skewness	15.25	-0.09	15.35	-0.17
Mount Grace Priory	AIC	-4428.79	1966.17	-4482.04	1947.10
Mount Grace Priory	BIC	-4415.18	1979.78	-4468.44	1960.71
Mount Grace Priory	Adj R-sq.	0.24	0.54	0.3 0	0.55
Mount Grace Priory	Skewness	8.73	-0.26	-0.28	8.49
Stokesay Castle	AIC	-4433.55	1414.31	-4492.93	1399.59
Stokesay Castle	BIC	-4420.90	1426.95	-4480.28	1412.24
Stokesay Castle	Adj. R Sq.	0.32	0.35	0.39	0.37
Stokesay Castle	Skewness	4.54	-0.33	4.13	-0.34

Table A2: Comparison of statistical models across various sites for Huq mobile analytical data.

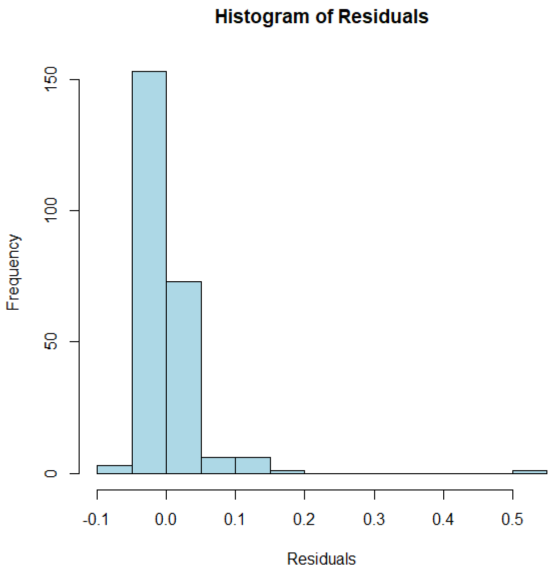
Site	Metric	Linear	Log-Linear	Linear-Log	Log-Log
Audley End	AIC	-837.92	829.42	-853.71	806.52
Audley End	BIC	-827.12	840.17	-842.96	817.27
Audley End	Adj. R-sq.	0.16	0.46	0.21	0.50
Audley End	Skewness	7.38	-0.42	7.06	-0.33
Belsay Hall	AIC	-353.55	270.08	-356.58	265.13
Belsay Hall	BIC	-345.59	278.05	-348.62	273.09
Belsay Hall	Adj. R-sq.	0.14	0.52	0.16	0.54
Belsay Hall	Skewness	5.24	0.26	5.22	0.19
Eltham Palace	AIC	-6111.89	2798.02	-6150.72	2761.05
Eltham Palace	BIC	-6097.42	2812.49	-6136.25	2775.52
Eltham Palace	Adj. R-sq.	0.17	0.46	0.20	0.48
Eltham Palace	Skewness	7.65	0.06	7.66	0.04
Mount Grace Priory	AIC	-4589.63	1349.06	-4644.72	1311.97
Mount Grace Priory	BIC	-4577.07	1361.62	-4632.16	1324.52
Mount Grace Priory	Adj. R-sq.	0.35	0.47	0.42	0.51
Mount Grace Priory	Skewness	3.01	0.036	2.82	0.078
Stokesay Castle	AIC	-1330.08	492.83	-1345.87	476.51
Stokesay Castle	BIC	-1320.99	501.92	-1336.78	485.60
Stokesay Castle	Adj. R-sq.	0.17	0.41	0.25	0.47
Stokesay Castle	Skewness	7.85	0.29	7.58	0.29

13.2 Appendix B

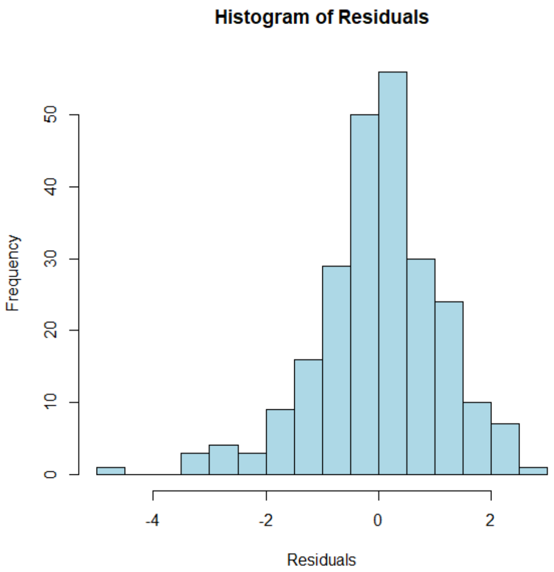
The below figures demonstrate the histogram of the residuals for all four specifications of models, ran under opportunity cost 4. These show the issues of skewness in models, which included a linear variable as the dependent variable, for both English Heritage and the mobile analytical data.

These figures support the reasoning for using the log-log model in the main analysis, alongside the goodness of fit scores observed in Appendix A and in the main text.

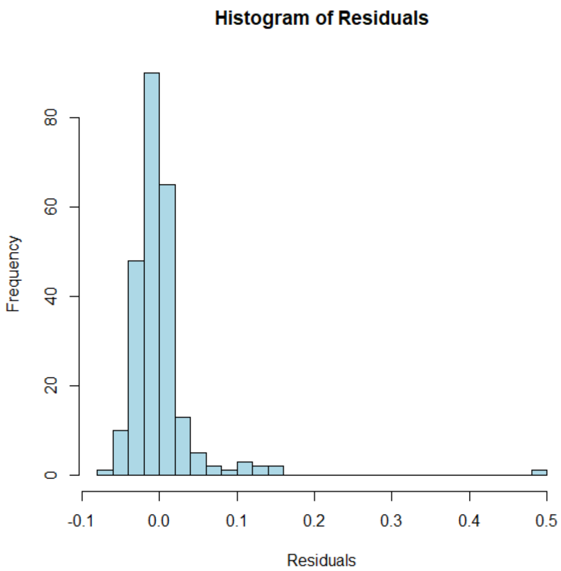
Linear



Log-Linear



Linear-Log



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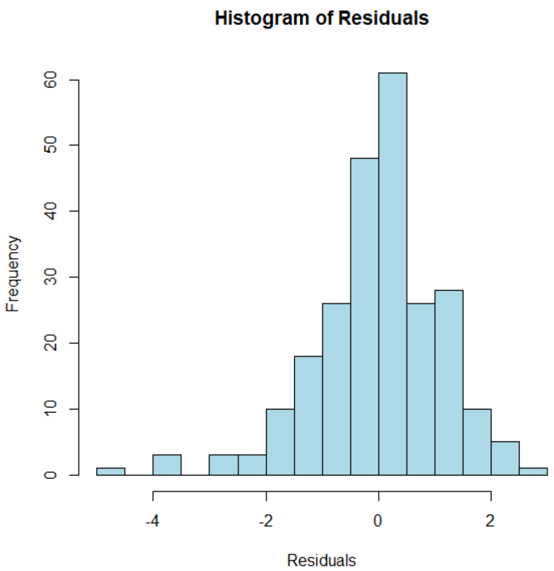

Figures B1-B4: Histograms of the residuals for Audley End using English Heritage data.

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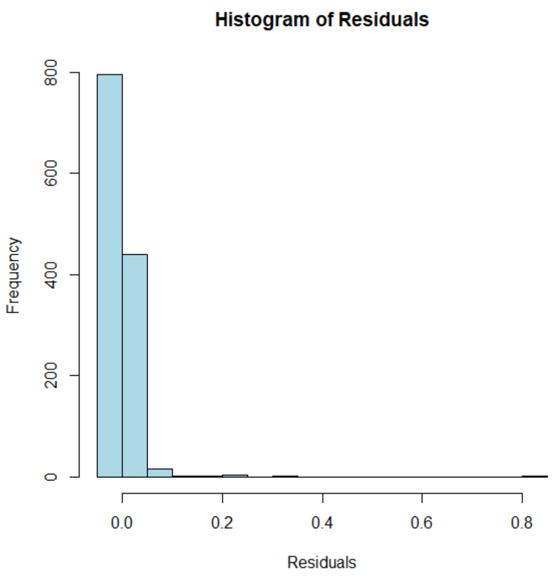
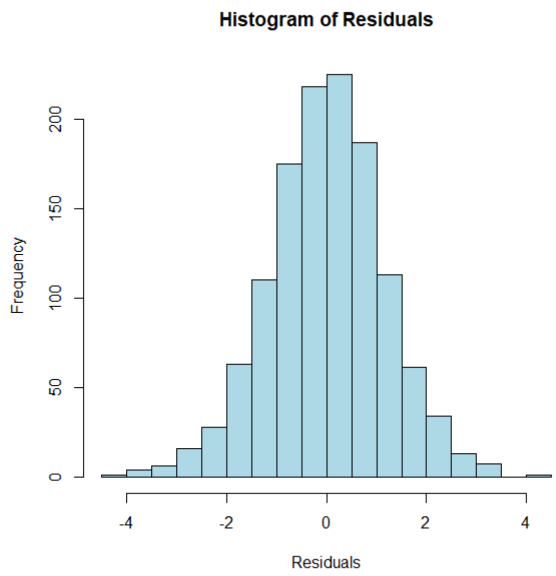
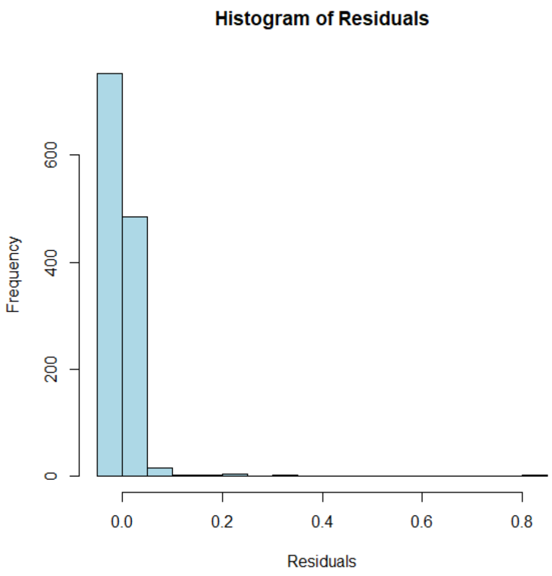


Log-Linear



Linear-Log



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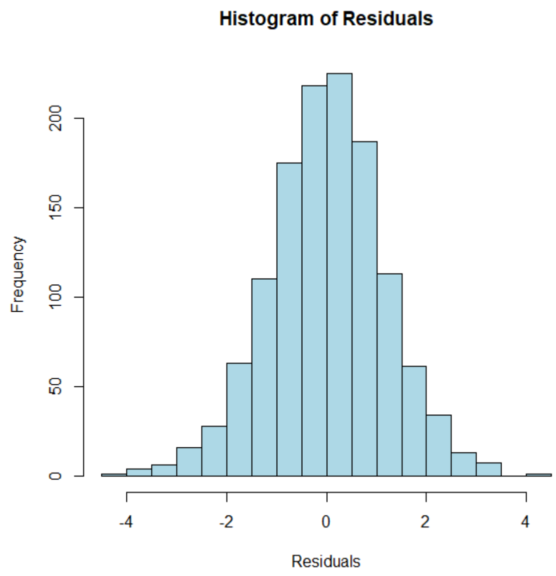
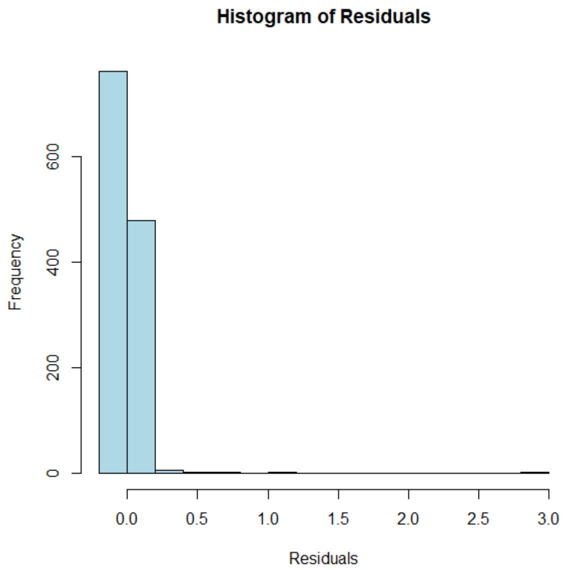
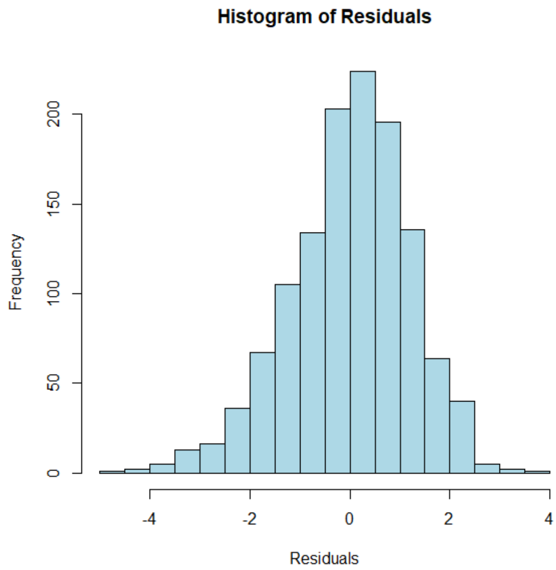


Figures B5-B8: Histograms of the residuals for Belsay Hall using English Heritage data.

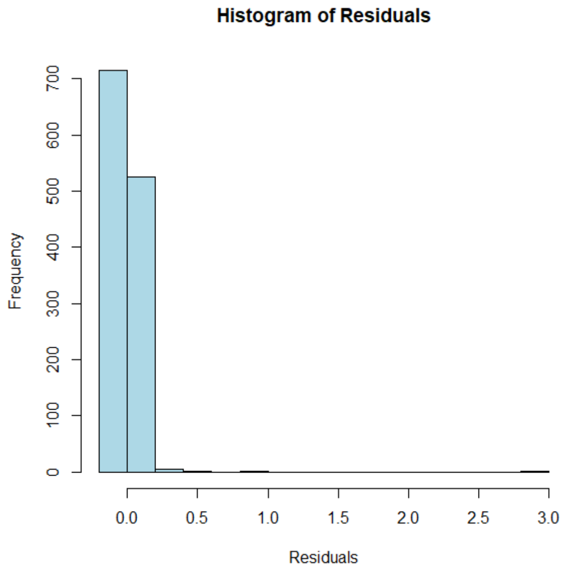
Linear



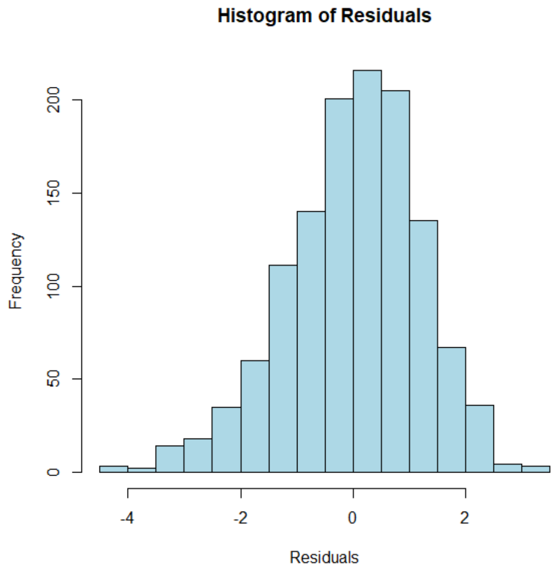
Log-Linear



Linear-Log

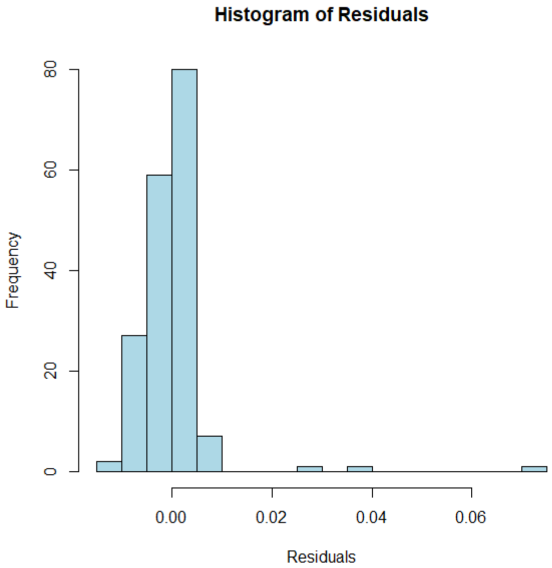


Log-Log

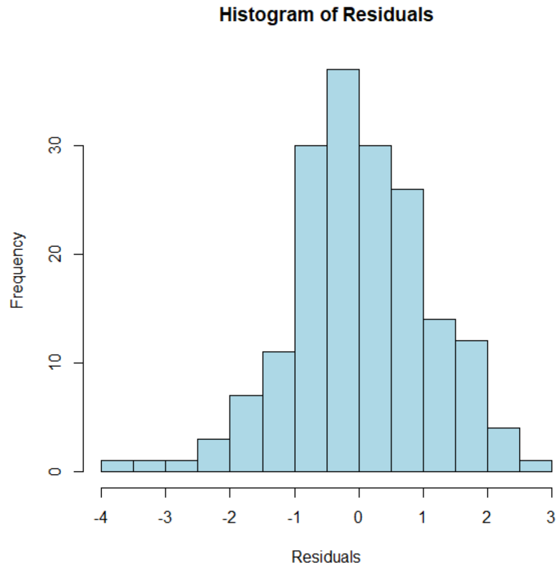


Figures B9-B12: Histograms of the residuals for Eltham Palace using English Heritage data.

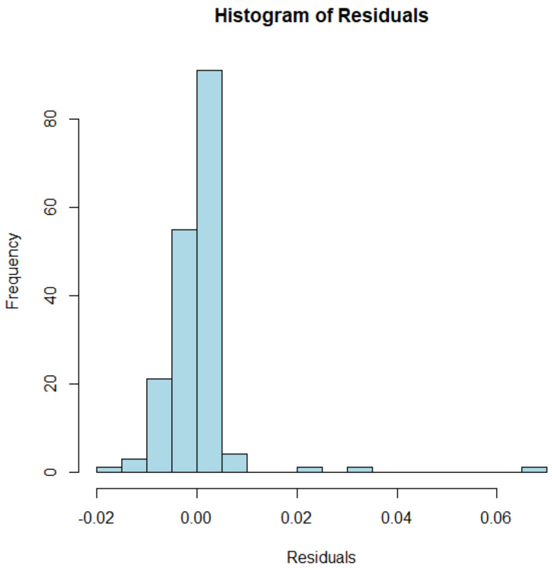
Linear



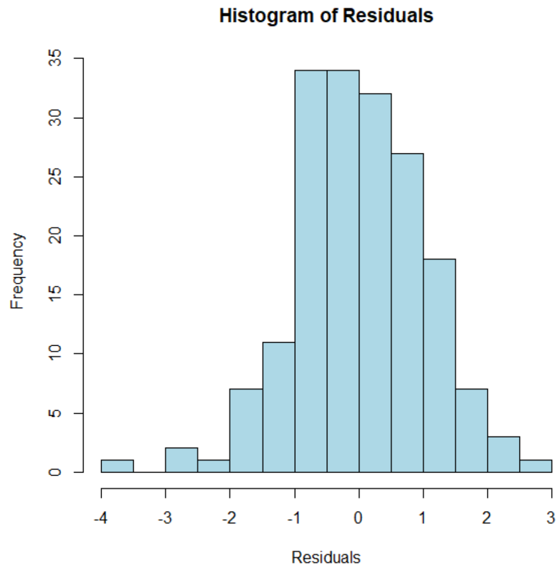
Log-Linear



Linear-Log

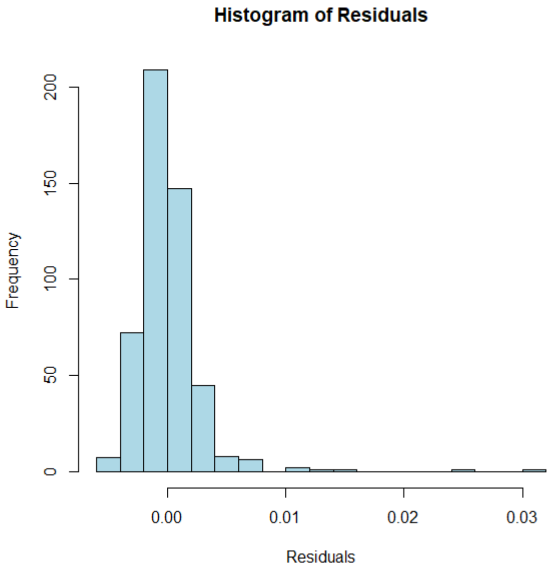


Log-Log

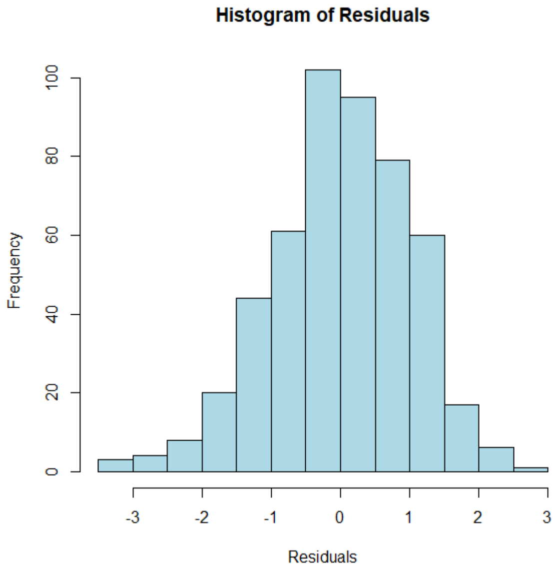


Figures B13-B16: Histograms of the residuals for Furness Abbey using English Heritage data.

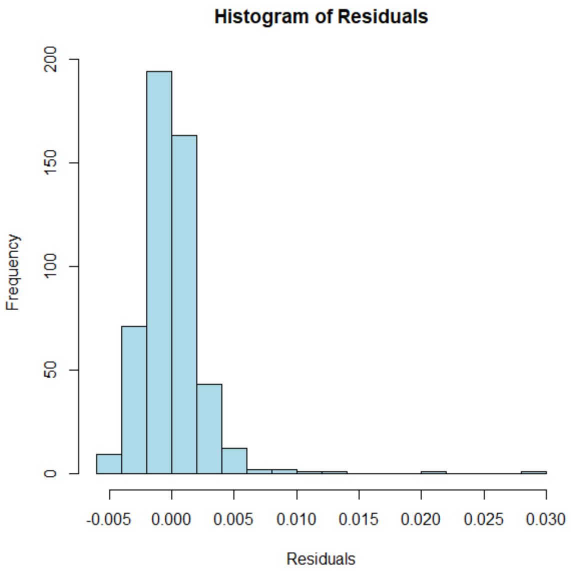
Linear



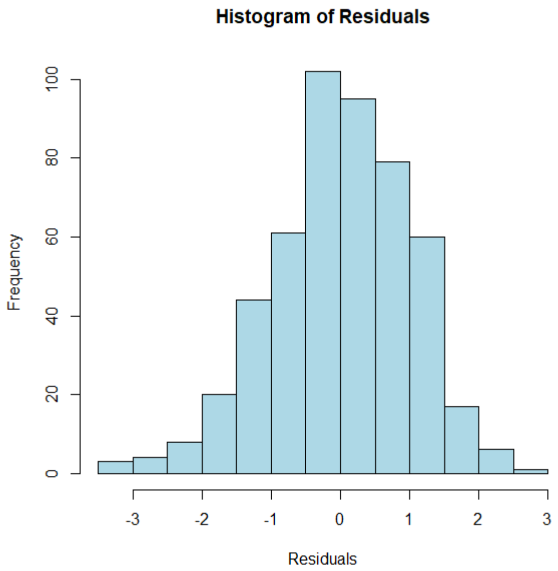
Log-Linear



Linear-Log

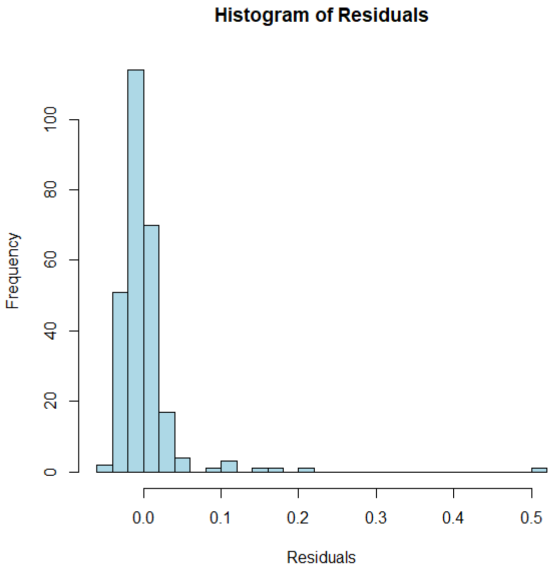


Log-Log

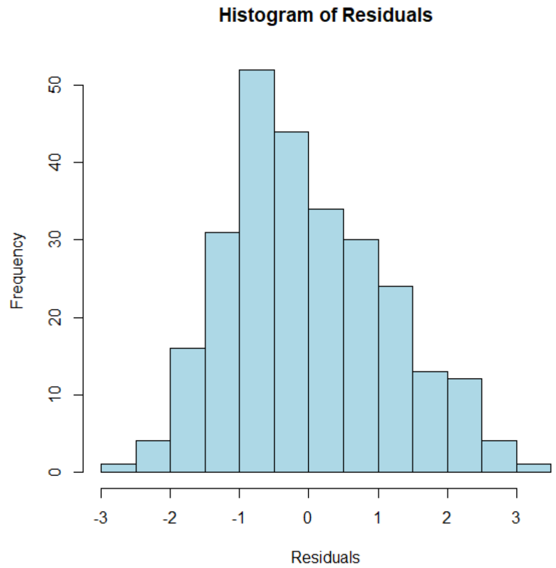


Figures B17-B20: Histograms of the residuals for Stokesay Castle using English Heritage data.

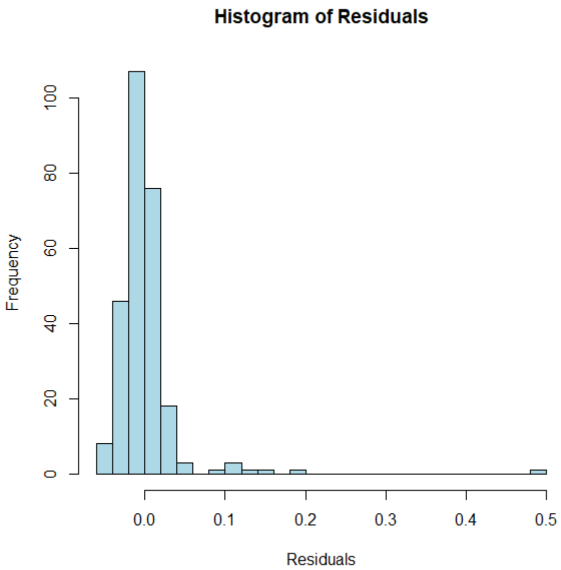
Linear



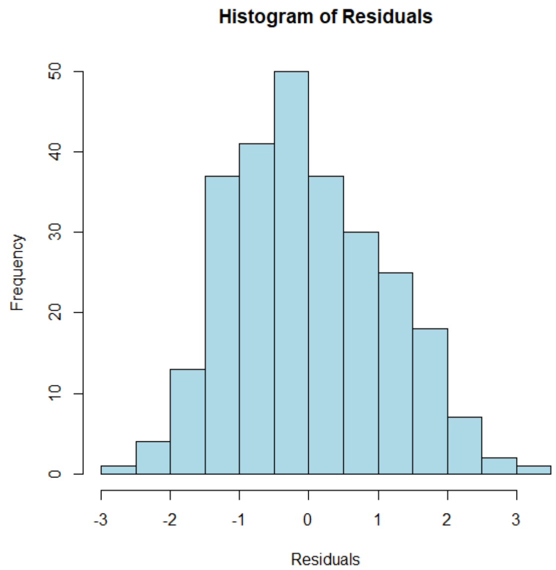
Log-Linear



Linear-Log

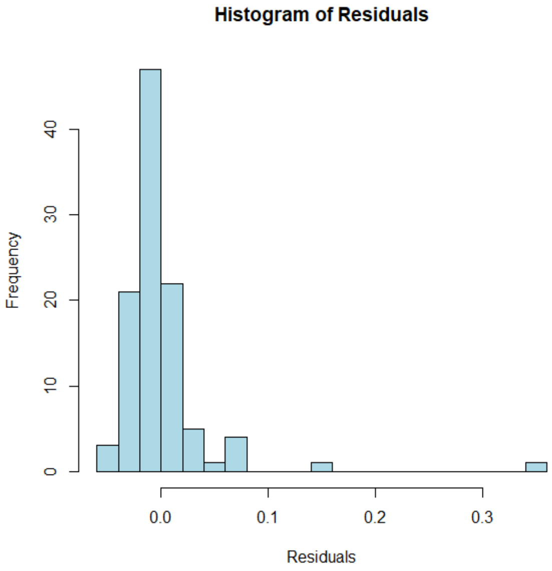


Log-Log

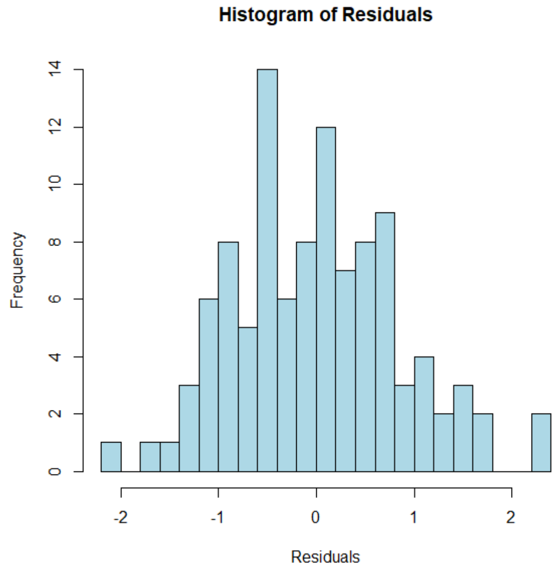


Figures B21-B24: Histograms of the residuals for Audley End using mobile analytical data.

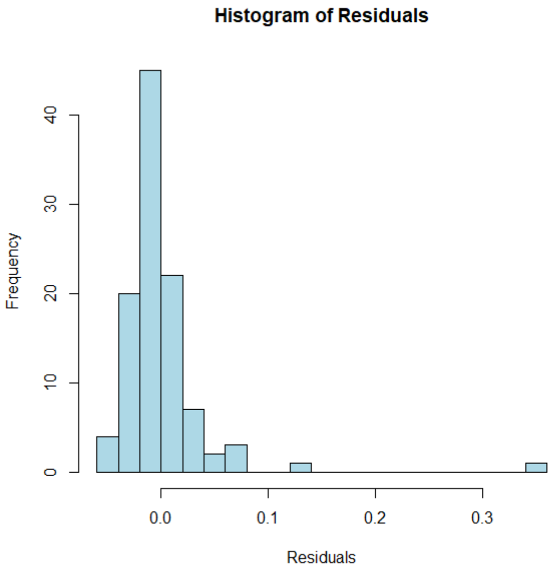
Linear



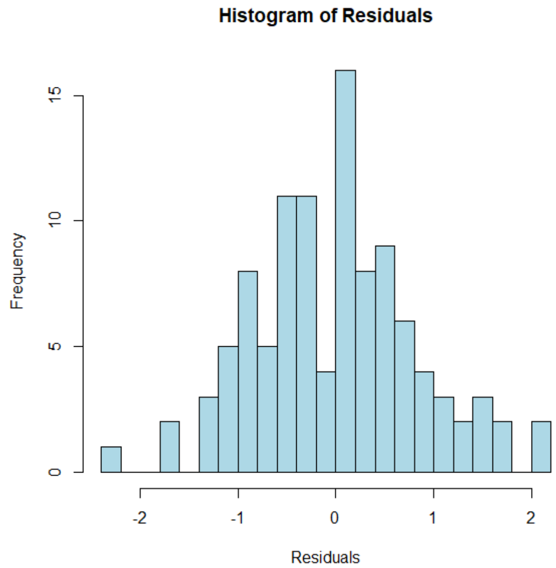
Log-Linear



Linear-Log

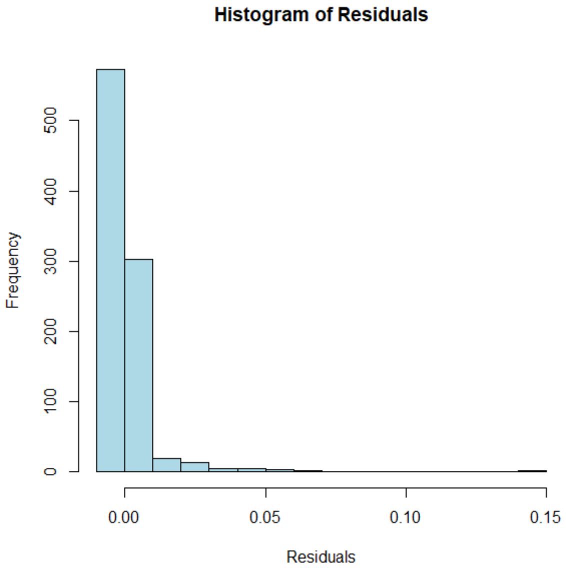


Log-Log

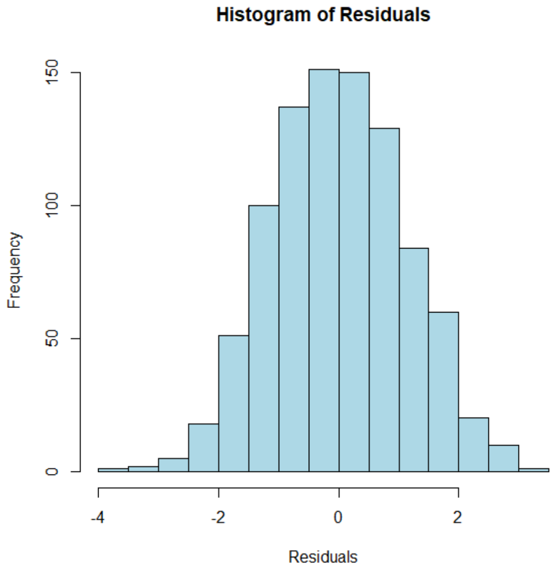


Figures B25-B28: Histograms of the residuals for Belsay Hall using mobile analytical data.

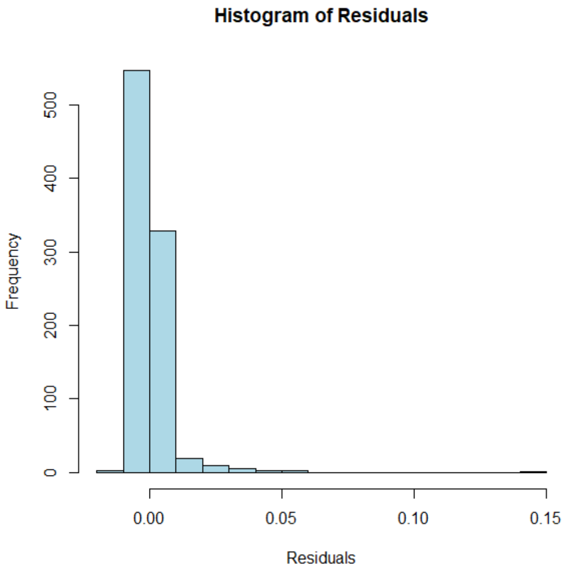
Linear



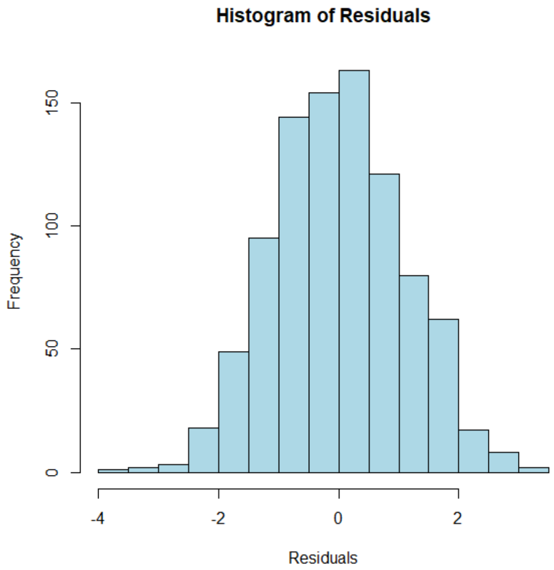
Log-Linear



Linear-Log

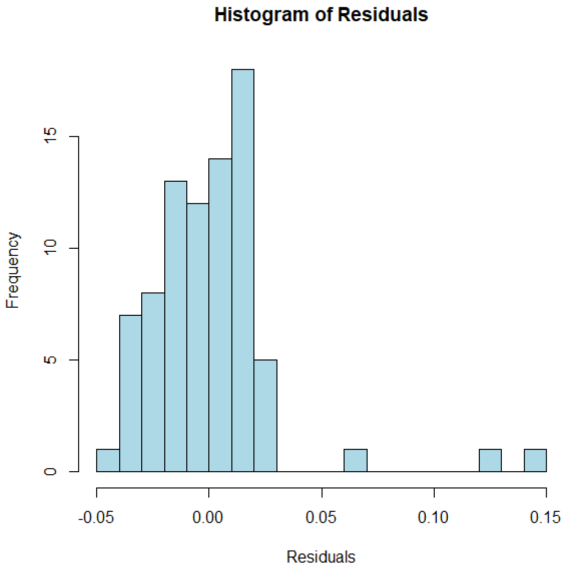


Log-Log

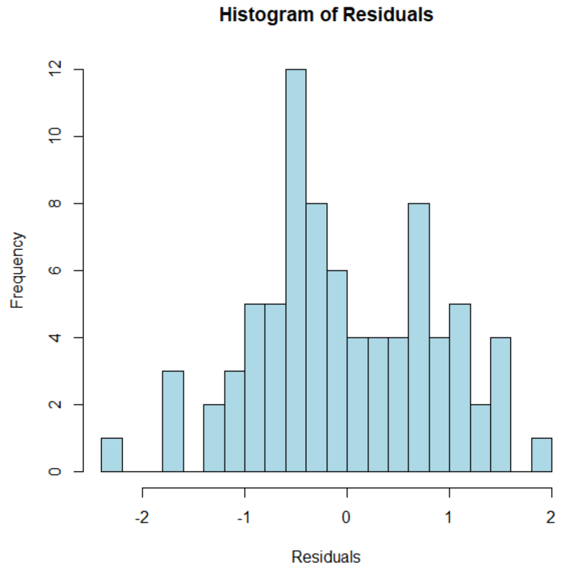


Figures B29-B32: Histograms of the residuals for Eltham Palace using mobile analytical data.

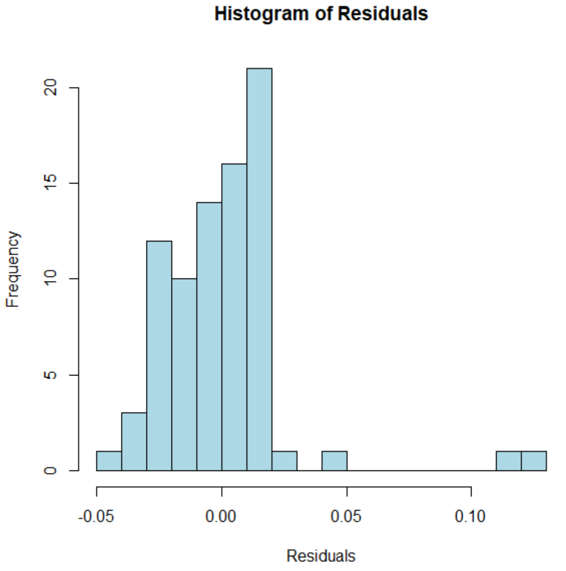
Linear



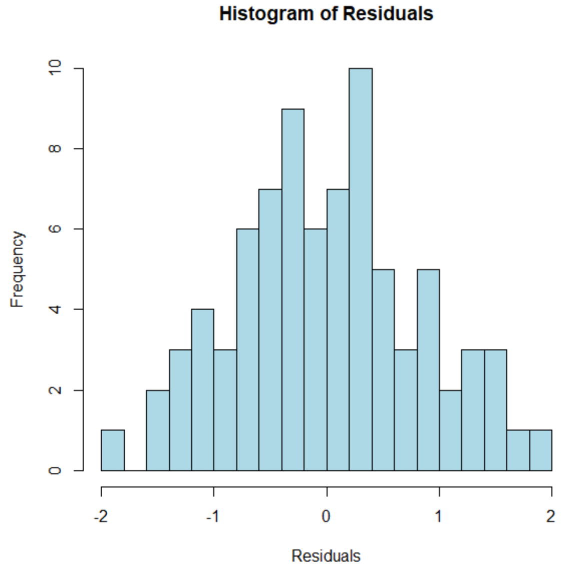
Log-Linear



Linear-Log

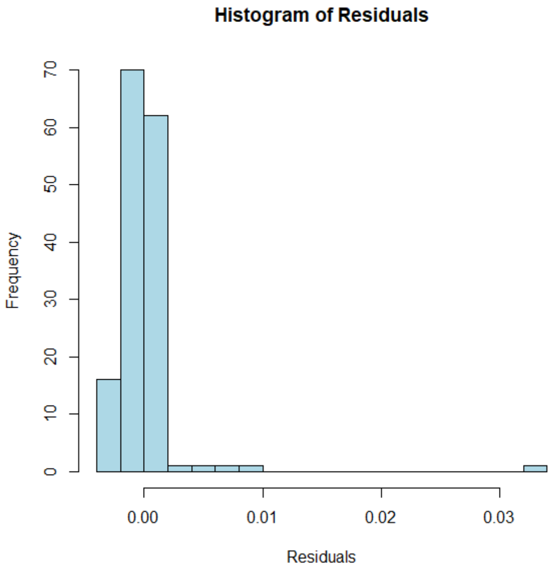


Log-Log

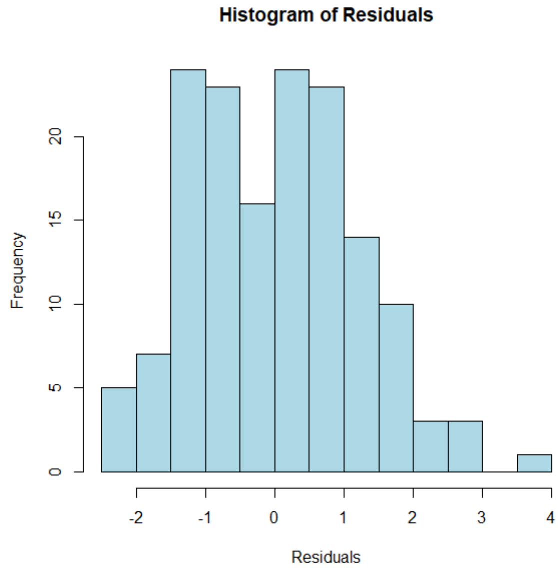


Figures B33-B36: Histograms of the residuals for Furness Abbey using mobile analytical data.

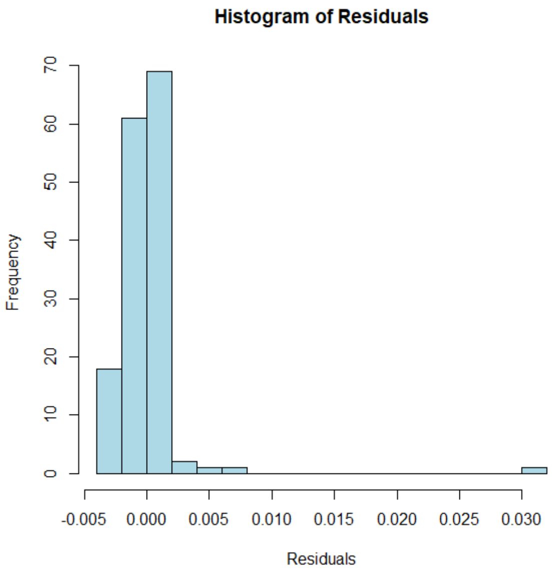
Linear



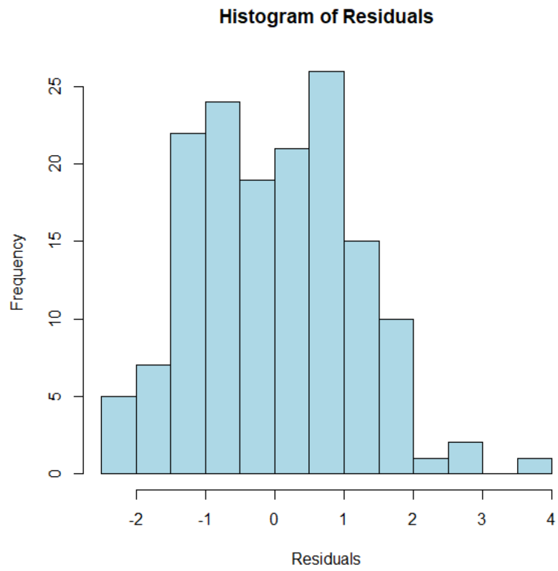
Log-Linear



Linear-Log



Log-Log



Figures B37-B40: Histograms of the residuals for Stokesay Castle using mobile analytical data.

13.3 Appendix C

The tables below show the regression results for all 10 sites, under the four different specifications and 4 different opportunity costs. There is a different interpretation for the coefficients under the four different specifications, so direct comparison is cautioned. It is however noticeable that cost and income remain significant across most variables for the English Heritage sites, with a lower degree in the mobile analytical.

It should also be noted that as the percentage attributed to opportunity cost increases, we see a decrease in the coefficient value. This suggests that as we value time higher, we reduce the elasticity of the reaction to price.

The following tables have a p-value represented by asterisks in the following way:

* for p < 0.05, ** for p < 0.01, *** for p < 0.001.

The numbers 1-4 refer to the opportunity cost used.

Table C1: Audley End English Heritage regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	-0.1388	-0.547 ***	-0.8472 ***	0.2012
Linear	Cost	-0.0076 ***	-0.0053 ***	-0.0034 ***	-0.0058 ***
Linear	Income (ln)	0.0371 ***	0.0723 ***	0.0979 ***	0.0024
Log-Linear	Intercept	-5.8245 ***	-21.0886 ***	-32.0848 ***	7.0289 ***
Log-Linear	Cost	-0.2892 ***	-0.1978 ***	-0.1277 ***	-0.2208 ***
Log-Linear	Income (ln)	0.8561 ***	2.1629 ***	3.0916 ***	-0.4559 **
Linear-Log	Intercept	0.4989 **	0.0388	-0.2988 ***	0.8277 **
Linear-Log	Cost	-0.259 ***	-0.2228 ***	-0.1942 ***	-0.2329 ***
Linear-Log	Income (ln)	0.0383 ***	0.0743 ***	0.1012 ***	0.002
Log-Log	Intercept	16.047 ***	0.1133	-10.6761 ***	26.3491 ***
Log-Log	Cost (ln)	-8.8458 ***	-7.2999 ***	-6.0751 ***	-7.7271 ***
Log-Log	Income (ln)	0.8057 ***	1.949 ***	2.6993 ***	-0.4242 **

Table C2: Belsay Hall English Heritage regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	-0.9144 **	-1.0347 ***	-1.1363 ***	-0.7837 **
Linear	Cost	-0.0054 ***	-0.004 ***	-0.0028 ***	-0.0038 ***
Linear	Income (ln)	0.1024 ***	0.1126 ***	0.1213 ***	0.088 **
Log-Linear	Intercept	-35.0433 ***	-40.7381 ***	-45.3917 ***	-28.5744 ***
Log-Linear	Cost	-0.2694 ***	-0.1949 ***	-0.1331 ***	-0.1908 ***
Log-Linear	Income (ln)	3.4841 ***	3.9578 ***	4.3433 ***	2.7774 ***
Linear-Log	Intercept	-0.6215 *	-0.7507 **	-0.8562 **	-0.4949 *
Linear-Log	Cost	-0.1214 ***	-0.1061 ***	-0.0927 ***	-0.1035 ***
Linear-Log	Income (ln)	0.0985 ***	0.1082 ***	0.1162 ***	0.0828 **
Log-Log	Intercept	-20.7078 ***	-26.9064 ***	-31.7248 ***	-14.7598 ***
Log-Log	Cost (ln)	-5.8309 ***	-4.9722 ***	-4.2405 ***	-4.9152 ***
Log-Log	Income (ln)	3.2546 ***	3.6814 ***	4.0128 ***	2.4955 ***

Table C3: Eltham Palace English Heritage regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	0.0723	-0.016	-0.0932 *	0.1357 ***
Linear	Cost	-0.0019 ***	-0.0015 ***	-0.001 ***	-0.0015 ***
Linear	Income (ln)	-0.0013	0.0066	0.0135 ***	-0.0077 *
Log-Linear	Intercept	-9.1732 ***	-18.2392 ***	-25.6256 ***	-3.04
Log-Linear	Cost	-0.1966 ***	-0.1421 ***	-0.0957 ***	-0.1545 ***
Log-Linear	Income (ln)	0.7504 ***	1.5486 ***	2.1928 ***	0.1258
Linear-Log	Intercept	0.1927 ***	0.0923 **	0.003	0.2563 ***
Linear-Log	Cost	-0.0548 ***	-0.0506 ***	-0.0458 ***	-0.051 ***
Linear-Log	Income (ln)	-0.0007	0.0084 *	0.0163 ***	-0.0072 *
Log-Log	Intercept	1.3108	-8.9036 ***	-16.9587 ***	6.2767 **
Log-Log	Cost (ln)	-5.1521 ***	-4.4593 ***	-3.8092 ***	-4.621 ***
Log-Log	Income (ln)	0.8528 ***	1.6851 ***	2.325 ***	0.2805

Table C4: Mount Grace Priory English Heritage regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	-0.1538 ***	-0.1879 ***	-0.2171 ***	-0.1242 ***
Linear	Cost	-0.0011 ***	-0.0008 ***	-0.0006 ***	-0.0008 ***
Linear	Income (ln)	0.0179 ***	0.0209 ***	0.0235 ***	0.0147 ***
Log-Linear	Intercept	-40.1902 ***	-46.7006 ***	-52.0903 ***	-34.3697 ***
Log-Linear	Cost	-0.2166 ***	-0.1587 ***	-0.1091 ***	-0.1531 ***
Log-Linear	Income (ln)	3.7637 ***	4.3349 ***	4.8041 ***	3.1326 ***
Linear-Log	Intercept	-0.0945 ***	-0.1323 ***	-0.1641 ***	-0.0685 ***
Linear-Log	Cost	-0.0276 ***	-0.0245 ***	-0.0216 ***	-0.0237 ***
Linear-Log	Income (ln)	0.018 ***	0.0212 ***	0.0238 ***	0.0148 ***
Log-Log	Intercept	-29.0852 ***	-35.9229 ***	-41.3812 ***	-24.5419 ***
Log-Log	Cost (ln)	-5.0002 ***	-4.3202 ***	-3.7148 ***	-4.2362 ***
Log-Log	Income (ln)	3.7133 ***	4.2422 ***	4.6611 ***	3.1201 ***

Table C5: Stokesay Castle English Heritage regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	-0.0461 ***	-0.0661 ***	-0.0817 ***	-0.024 ***
Linear	Cost	-0.0005 ***	-0.0004 ***	-0.0002 ***	-0.0004 ***
Linear	Income (ln)	0.0057 ***	0.0075 ***	0.0089 ***	0.0035 ***
Log-Linear	Intercept	-35.2931 ***	-42.194 ***	-47.4185 ***	-27.4118 ***
Log-Linear	Cost	-0.1795 ***	-0.1252 ***	-0.0828 ***	-0.1287 ***
Log-Linear	Income (ln)	3.117 ***	3.7359 ***	4.2018 ***	2.3228 ***
Linear-Log	Intercept	-0.0202 ***	-0.0389 ***	-0.0523 ***	0.0015
Linear-Log	Cost	-0.0119 ***	-0.0106 ***	-0.0096 ***	-0.0107 ***
Linear-Log	Income (ln)	0.0057 ***	0.0074 ***	0.0086 ***	0.0035 ***
Log-Log	Intercept	-26.245 ***	-32.4295 ***	-36.5978 ***	-19.199 ***
Log-Log	Cost (ln)	-3.9867 ***	-3.4602 ***	-3.0294 ***	-3.5026 ***
Log-Log	Income (ln)	3.0464 ***	3.5616 ***	3.9104 ***	2.3022 ***

Table C6: Dover Castle English Heritage regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	-0.1141 *	-0.3078 ***	-0.4418 ***	0.1354 *
Linear	Cost	-0.0046 ***	-0.0032 ***	-0.0021 ***	-0.0035 ***
Linear	Income (ln)	0.0247 ***	0.0414 ***	0.0528 ***	-0.0002
Log-Linear	Intercept	-19.8514 ***	-29.361 ***	-36.1391 ***	-8.0442 ***
Log-Linear	Cost	-0.2137 ***	-0.148 ***	-0.0969 ***	-0.1587 ***
Log-Linear	Income (ln)	1.9585 ***	2.7911 ***	3.3772 ***	0.7764 ***
Linear-Log	Intercept	0.152 **	-0.0319	-0.1524 ***	0.3519 ***
Linear-Log	Cost	-0.1199 ***	-0.102 ***	-0.0877 ***	-0.1052 ***
Linear-Log	Income (ln)	0.0248 ***	0.0388 ***	0.0478 ***	0.0029
Log-Log	Intercept	-5.7937 **	-13.3188 ***	-17.8684 ***	2.9653
Log-Log	Cost (ln)	-5.0988 ***	-4.2946 ***	-3.6372 ***	-4.3866 ***
Log-Log	Income (ln)	1.6592 ***	2.2133 ***	2.5243 ***	0.6785 **

Table C7: Goodrich Castle English Heritage regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	-0.0556 ***	-0.0826 ***	-0.1039 ***	-0.0312 ***
Linear	Cost	-0.0007 ***	-0.0005 ***	-0.0003 ***	-0.0005 ***
Linear	Income (ln)	0.0071 ***	0.0096 ***	0.0115 ***	0.0047 ***
Log-Linear	Intercept	-41.9802 ***	-48.5422 ***	-53.7421 ***	-36.0593 ***
Log-Linear	Cost	-0.1653 ***	-0.119 ***	-0.0803 ***	-0.121 ***
Log-Linear	Income (ln)	3.7473 ***	4.3381 ***	4.8022 ***	3.1417 ***
Linear-Log	Intercept	-0.0198 **	-0.0475 ***	-0.069 ***	0.0041
Linear-Log	Cost	-0.0167 ***	-0.015 ***	-0.0135 ***	-0.0151 ***
Linear-Log	Income (ln)	0.0072 ***	0.0097 ***	0.0116 ***	0.0047 ***
Log-Log	Intercept	-33.6144 ***	-39.7881 ***	-44.3966 ***	-28.4222 ***
Log-Log	Cost (ln)	-3.7573 ***	-3.3197 ***	-2.9296 ***	-3.3236 ***
Log-Log	Income (ln)	3.7036 ***	4.2319 ***	4.626 ***	3.1391 ***

Table C8: Furness Abbey English Heritage regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	0.1239	0.0847	0.051	0.1679
Linear	Cost	-0.0011 ***	-0.0008 ***	-0.0006 ***	-0.0008 ***
Linear	Income (ln)	-0.0093	-0.0056	-0.0025	-0.0136
Log-Linear	Intercept	-11.8505	-18.5536 **	-24.1954 **	-4.2612
Log-Linear	Cost	-0.1858 ***	-0.137 ***	-0.0948 ***	-0.1346 ***
Log-Linear	Income (ln)	0.8757	1.4957 *	2.0153**	0.1138
Linear-Log	Intercept	0.1606	0.1247	0.0951	0.193 *
Linear-Log	Cost	-0.0225 ***	-0.0206 ***	-0.0186 ***	-0.0205 ***
Linear-Log	Income (ln)	-0.0084	-0.0051	-0.0023	-0.0117
Log-Log	Intercept	-5.5545	-11.1143	-15.4117 *	-0.6744
Log-Log	Cost (ln)	-3.5735 ***	-3.1664 ***	-2.78 ***	-3.1168 ***
Log-Log	Income (ln)	0.9241	1.4083	1.7762 **	0.3879

Table C9: Whitby Abbey English Heritage regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	-0.0971 ***	-0.126 ***	-0.1487 ***	-0.0677 ***
Linear	Cost	-0.0008 ***	-0.0006 ***	-0.0004 ***	-0.0005 ***
Linear	Income (ln)	0.012 ***	0.0145 ***	0.0165 ***	0.0088 ***
Log-Linear	Intercept	-28.0315 ***	-32.3929 ***	-35.6819 ***	-23.4157 ***
Log-Linear	Cost	-0.1255 ***	-0.0878 ***	-0.0581 ***	-0.0842 ***
Log-Linear	Income (ln)	2.4879 ***	2.8671 ***	3.1501 ***	1.991 ***
Linear-Log	Intercept	-0.053 ***	-0.0821 ***	-0.1038 ***	-0.0295 *
Linear-Log	Cost	-0.0197 ***	-0.017 ***	-0.0147 ***	-0.0167 ***
Linear-Log	Income (ln)	0.0119 ***	0.0142 ***	0.0159 ***	0.009 ***
Log-Log	Intercept	-21.1861 ***	-25.4714 ***	-28.4947 ***	-17.7988 ***
Log-Log	Cost (ln)	-2.9567 ***	-2.4852 ***	-2.0983 ***	-2.4268 ***
Log-Log	Income (ln)	2.4384 ***	2.7545 ***	2.9722 ***	1.9964 ***

Table C10: Rievaulx Abbey English Heritage regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	-0.0831 ***	-0.107 ***	-0.1277 ***	-0.0582 ***
Linear	Cost	-0.0007 ***	-0.0006 ***	-0.0004 ***	-0.0005 ***
Linear	Income (ln)	0.0102 ***	0.0124 ***	0.0142 ***	0.0076 ***
Log-Linear	Intercept	-35.2846 ***	-41.5836 ***	-46.8523 ***	-28.6997 ***
Log-Linear	Cost	-0.1959 ***	-0.1439 ***	-0.0988 ***	-0.1401 ***
Log-Linear	Income (ln)	3.2732 ***	3.8311 ***	4.293 ***	2.5804 ***
Linear-Log	Intercept	-0.0372 ***	-0.0617 ***	-0.0821 ***	-0.0127
Linear-Log	Cost	-0.019 ***	-0.017 ***	-0.0152 ***	-0.0168 ***
Linear-Log	Income (ln)	0.0099 ***	0.0119 ***	0.0137 ***	0.0071 ***
Log-Log	Intercept	-23.8093 ***	-30.2236 ***	-35.3805 ***	-17.9387 ***
Log-Log	Cost (ln)	-4.8185 ***	-4.2295 ***	-3.6942 ***	-4.1835 ***
Log-Log	Income (ln)	3.1835 ***	3.6988 ***	4.1117 ***	2.5019 ***

Table C11: Audley End Huq regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	0.1498	-0.0721	-0.2405	0.3149
Linear	Cost	-0.0053 ***	-0.0036 ***	-0.0024 ***	-0.0039 ***
Linear	Income (ln)	0.0016	0.02	0.0339 *	-0.0161
Log-Linear	Intercept	29.4171 ***	18.2861 **	9.8353	37.4934 ***
Log-Linear	Cost	-0.2659 ***	-0.1817 ***	-0.118 ***	-0.1965 ***
Log-Linear	Income (ln)	-2.6056 ***	-1.6829 **	-0.9846	-3.4791 ***
Linear-Log	Intercept	0.651 *	0.4113	0.2455	0.8179 *
Linear-Log	Cost	-0.1656 ***	-0.1374 ***	-0.116 ***	-0.1436 ***
Linear-Log	Income (ln)	-0.0078	0.0082	0.0193	-0.0288
Log-Log	Intercept	50.1734 ***	37.8205 ***	29.0667 ***	56.4511 ***
Log-Log	Cost (ln)	-7.7244 ***	-6.2476 ***	-5.1053 ***	-6.5451 ***
Log-Log	Income (ln)	-2.8471 ***	-2.0423 ***	-1.4809 **	-3.7324 ***

Table C12: Belsay Hall Huq regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	-0.5363	-0.6119	-0.676	-0.4586
Linear	Cost	-0.0048 ***	-0.0035 ***	-0.0024 ***	-0.0034 ***
Linear	Income (ln)	0.0634	0.0694	0.0745	0.0544
Log-Linear	Intercept	-11.1694	-15.0482 *	-18.2363 **	-7.1504
Log-Linear	Cost	-0.2479 ***	-0.1792 ***	-0.1224 ***	-0.175 ***
Log-Linear	Income (ln)	1.1052	1.4083 *	1.6567 **	0.6408
Linear-Log	Intercept	-0.2928	-0.3892	-0.4718	-0.2029
Linear-Log	Cost	-0.1057 ***	-0.0923 ***	-0.0803 ***	-0.0899 ***
Linear-Log	Income (ln)	0.0609	0.0677	0.0737	0.0491
Log-Log	Intercept	0.7133	-4.295	-8.3918	4.8513
Log-Log	Cost (ln)	-5.2098 ***	-4.4216 ***	-3.7513 ***	-4.3615 ***
Log-Log	Income (ln)	0.9745	1.2978 *	1.568 **	0.4011

Table C13: Eltham Palace Huq regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	0.1027 ***	0.0725 ***	0.0465 ***	0.1246 ***
Linear	Cost	-0.0007 ***	-0.0005 ***	-0.0004 ***	-0.0006 ***
Linear	Income (ln)	-0.0076 ***	-0.0049 **	-0.0026	-0.0098 ***
Log-Linear	Intercept	23.5403 ***	15.4929 ***	8.7392 ***	28.9961 ***
Log-Linear	Cost	-0.1956 ***	-0.1430 ***	-0.0971 ***	-0.1531 ***
Log-Linear	Income (ln)	-2.3950 ***	-1.6898 ***	-1.1040 ***	-2.9579 ***
Linear-Log	Intercept	0.1456 ***	0.1107 ***	0.0806 ***	0.1664 ***
Linear-Log	Cost	-0.0200 ***	-0.0180 ***	-0.0158 ***	-0.0184 ***
Linear-Log	Income (ln)	-0.0073 ***	-0.0044 **	-0.0018	-0.0096 ***
Log-Log	Intercept	33.4220 ***	24.2185 ***	16.7256 ***	37.7520 ***
Log-Log	Cost (ln)	-4.9793 ***	-4.3083 ***	-3.6638 ***	-4.4409 ***
Log-Log	Income (ln)	-2.2861 ***	-1.5470 ***	-0.9625 ***	-2.8038 ***

Table C14: Mount Grace Priory Huq regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	0.0111	0.0020	-0.0057	0.0183 *
Linear	Cost	-0.0003 ***	-0.0002 ***	-0.0002 ***	-0.0002 ***
Linear	Income (ln)	-0.0002	0.0006	0.0013	-0.0010
Log-Linear	Intercept	-3.4094	-8.6664	-13.1829 **	0.7811
Log-Linear	Cost	-0.1872 ***	-0.1393 ***	-0.0971 ***	-0.1338 ***
Log-Linear	Income (ln)	0.0306	0.4936	0.8891 **	-0.4295
Linear-Log	Intercept	0.0274 ***	0.0170 *	0.0081	0.0338 ***
Linear-Log	Cost	-0.0077 ***	-0.0068 ***	-0.0060 ***	-0.0067 ***
Linear-Log	Income (ln)	-0.0002	0.0007	0.0014	-0.0010
Log-Log	Intercept	5.6732	-0.1301	-5.0107	9.1320 **
Log-Log	Cost (ln)	-4.3027 ***	-3.7654 ***	-3.2732 ***	-3.6926 ***
Log-Log	Income (ln)	0.0312	0.4933	0.8823 **	-0.4205

Table C15: Stokesay Castle Huq regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	0.0058	-0.0037	-0.0112	0.0182
Linear	Cost	-0.0003 *	-0.0002 *	-0.0002 *	-0.0002 *
Linear	Income (ln)	0.0002	0.0011	0.0017	-0.0010
Log-Linear	Intercept	12.9340	6.1284	0.7870	21.9351
Log-Linear	Cost	-0.2456 ***	-0.1721 ***	-0.1144 ***	-0.1723 ***
Log-Linear	Income (ln)	-1.5535	-0.9600	-0.4954	-2.4794 *
Linear-Log	Intercept	0.0278	0.0184	0.0117	0.0424 *
Linear-Log	Cost	-0.0081 *	-0.0071 *	-0.0064 *	-0.0071 *
Linear-Log	Income (ln)	-0.0002	0.0006	0.0011	-0.0018
Log-Log	Intercept	25.1300 *	18.2245	13.2487	33.6021 **
Log-Log	Cost (ln)	-5.2267 ***	-4.4959 ***	-3.8993 ***	-4.5145 ***
Log-Log	Income (ln)	-1.7020	-1.1569	-0.7597	-2.6300 *

Table C16: Dover Castle Huq regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	0.7316	0.5184	0.3787	0.9963 *
Linear	Cost	-0.0079 ***	-0.0053 ***	-0.0034 ***	-0.0060 ***
Linear	Income (ln)	-0.0400	-0.0253	-0.0161	-0.0686
Log-Linear	Intercept	-0.7671	-9.1450	-14.9411 *	9.7801
Log-Linear	Cost	-0.2650 ***	-0.1809 ***	-0.1176 ***	-0.1964 ***
Log-Linear	Income (ln)	0.4687	1.0899	1.5073 *	-0.6756
Linear-Log	Intercept	1.3072 **	0.9190 *	0.6169	1.4788 **
Linear-Log	Cost	-0.2900 ***	-0.2327 ***	-0.1900 ***	-0.2487 ***
Linear-Log	Income (ln)	-0.0234	-0.0024	0.0150	-0.0507
Log-Log	Intercept	22.0616 ***	10.7976 *	3.1336	28.7490 ***
Log-Log	Cost (ln)	-8.9568 ***	-7.0869 ***	-5.6388 ***	-7.3756 ***
Log-Log	Income (ln)	0.4313	0.9743	1.3053 *	-0.6529

Table C17: Goodrich Castle Huq regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	0.0202	0.0024	-0.0120	0.0394 **
Linear	Cost	-0.0006 ***	-0.0004 ***	-0.0003 ***	-0.0004 ***
Linear	Income (ln)	-0.0005	0.0011	0.0024	-0.0024
Log-Linear	Intercept	6.6764	0.9261	-3.7336	12.7829 **
Log-Linear	Cost	-0.1908 ***	-0.1375 ***	-0.0934 ***	-0.1387 ***
Log-Linear	Income (ln)	-0.9181 *	-0.4116	-0.0031	-1.5500 ***
Linear-Log	Intercept	0.0512 **	0.0314 *	0.0153	0.0715 **
Linear-Log	Cost	-0.0142 ***	-0.0128 ***	-0.0115 ***	-0.0128 ***
Linear-Log	Income (ln)	-0.0005	0.0012	0.0026	-0.0026 *
Log-Log	Intercept	15.7033 ***	9.8665 *	5.3676	21.1636 ***
Log-Log	Cost (ln)	-4.1239 ***	-3.6071 ***	-3.1565 ***	-3.6158 ***
Log-Log	Income (ln)	-0.9729 *	-0.4955	-0.1255	-1.5800 ***

Table C18: Furness Abbey Huq regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	1.0823 *	0.9334	0.8065	1.2343 *
Linear	Cost	-0.0052 ***	-0.0038 ***	-0.0027 ***	-0.0037 ***
Linear	Income (ln)	-0.0928	-0.0792	-0.0676	-0.1083 *
Log-Linear	Intercept	12.7333	3.7931	-3.7249	21.7388 *
Log-Linear	Cost	-0.3129 ***	-0.2298 ***	-0.1587 ***	-0.2202 ***
Log-Linear	Income (ln)	-1.2329	-0.4182	0.2644	-2.1674 *
Linear-Log	Intercept	1.1316 *	0.9626 *	0.8186	1.2107 *
Linear-Log	Cost	-0.0981 ***	-0.0870 ***	-0.0766 ***	-0.0857 ***
Linear-Log	Income (ln)	-0.0796	-0.0647	-0.0519	-0.0889 *
Log-Log	Intercept	15.5663	6.3320	-1.1383	19.7796
Log-Log	Cost (ln)	-5.4622 ***	-4.7344 ***	-4.0673 ***	-4.6201 ***
Log-Log	Income (ln)	-0.5580	0.2218	0.8449	-1.1067

Table C19: Whitby Abbey Huq regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	-0.3301	-1.0055	-1.5453	0.3262
Linear	Cost	-0.0192 ***	-0.0139 ***	-0.0094 ***	-0.0134 ***
Linear	Income (ln)	0.0843	0.1444	0.1921 *	0.0147
Log-Linear	Intercept	-9.9729 *	-17.2528 ***	-22.9868 ***	-2.6740
Log-Linear	Cost	-0.2119 ***	-0.1517 ***	-0.1023 ***	-0.1462 ***
Log-Linear	Income (ln)	1.1120 **	1.7547 ***	2.2571 ***	0.3339
Linear-Log	Intercept	0.6891	-0.0397	-0.6164	1.2762 **
Linear-Log	Cost	-0.4931 ***	-0.4352 ***	-0.3852 ***	-0.4279 ***
Linear-Log	Income (ln)	0.0922	0.1532 *	0.2023 *	0.0241
Log-Log	Intercept	1.4653	-5.6185	-10.7909 **	7.2630
Log-Log	Cost (ln)	-4.9805 ***	-4.2669 ***	-3.6543 ***	-4.1737 ***
Log-Log	Income (ln)	1.0366 **	1.5830 ***	1.9739 ***	0.3122

Table C20: Rievaulx Abbey Huq regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	-0.0140	-0.0327	-0.0492	0.0059
Linear	Cost	-0.0008 ***	-0.0006 ***	-0.0004 ***	-0.0006 ***
Linear	Income (ln)	0.0036	0.0052	0.0066	0.0014
Log-Linear	Intercept	-4.3772	-10.1914	-15.1976 *	1.5375
Log-Linear	Cost	-0.2549 ***	-0.1875 ***	-0.1294 ***	-0.1797 ***
Log-Linear	Income (ln)	0.3758	0.8717	1.2968	-0.2744
Linear-Log	Intercept	0.0324	0.0092	-0.0108	0.0539
Linear-Log	Cost	-0.0202 ***	-0.0177 ***	-0.0155 ***	-0.0174 ***
Linear-Log	Income (ln)	0.0033	0.0051	0.0067	0.0007
Log-Log	Intercept	8.4377	1.2667	-4.7396	14.2449
Log-Log	Cost (ln)	-5.8773 ***	-5.0855 ***	-4.3817 ***	-5.0119 ***
Log-Log	Income (ln)	0.3431	0.8853	1.3433	-0.3854

Table C21: Kenilworth Huq regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	-0.9932 **	-1.0786 **	-1.1484 **	-0.8830 **
Linear	Cost	-0.0042 ***	-0.0030 ***	-0.0021 ***	-0.0031 ***
Linear	Income (ln)	0.1054 **	0.1123 **	0.1179 **	0.0937 **
Log-Linear	Intercept	-19.4932 ***	-25.5196 ***	-30.2315 ***	-11.3373 *
Log-Linear	Cost	-0.3078 ***	-0.2172 ***	-0.1453 ***	-0.2291 ***
Log-Linear	Income (ln)	1.9360 ***	2.4052 ***	2.7699 ***	1.0689 *
Linear-Log	Intercept	-0.7048 *	-0.7930 **	-0.8603 **	-0.5796 **
Linear-Log	Cost	-0.1073 ***	-0.0943 ***	-0.0830 ***	-0.0942 ***
Linear-Log	Income (ln)	0.1005 **	0.1065 **	0.1111 **	0.0860 **
Log-Log	Intercept	0.4563	-6.0049	-10.5899 *	8.3705
Log-Log	Cost (ln)	-7.2920 ***	-6.1024 ***	-5.1166 ***	-6.2473 ***
Log-Log	Income (ln)	1.5171 ***	1.8771 ***	2.1157 ***	0.5384

Table C22: Bolsover Huq regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	0.0069	-0.0412	-0.0797	0.0363
Linear	Cost	-0.0017 ***	-0.0013 ***	-0.0009 ***	-0.0013 ***
Linear	Income (ln)	0.0039	0.0080	0.0112	0.0005
Log-Linear	Intercept	-2.8721	-9.5166	-14.8639 **	1.3397
Log-Linear	Cost	-0.2343 ***	-0.1710 ***	-0.1174 ***	-0.1703 ***
Log-Linear	Income (ln)	0.1584	0.7270	1.1804 *	-0.3216
Linear-Log	Intercept	0.0659	-0.0064	-0.0726	0.0839
Linear-Log	Cost	-0.0456 ***	-0.0401 ***	-0.0354 ***	-0.0401 ***
Linear-Log	Income (ln)	0.0080	0.0139	0.0195	0.0052
Log-Log	Intercept	7.6859	-0.4052	-7.0449	10.7006 *
Log-Log	Cost (ln)	-5.6342 ***	-4.8365 ***	-4.1349 ***	-4.7990 ***
Log-Log	Income (ln)	0.3101	0.9230	1.4263 **	-0.1585

Table C23: Farleigh Huq regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	0.1348	0.0978	0.0686	0.1915
Linear	Cost	-0.0016 ***	-0.0011 ***	-0.0007 ***	-0.0011 ***
Linear	Income (ln)	-0.0100	-0.0067	-0.0041	-0.0156
Log-Linear	Intercept	7.8371	-1.2559	-8.1320	19.4006 *
Log-Linear	Cost	-0.3514 ***	-0.2399 ***	-0.1562 ***	-0.2530 ***
Log-Linear	Income (ln)	-0.8878	-0.0799	0.5301	-2.0387 *
Linear-Log	Intercept	0.1990	0.1661	0.1426	0.2577
Linear-Log	Cost	-0.0263 ***	-0.0234 ***	-0.0210 ***	-0.0239 ***
Linear-Log	Income (ln)	-0.0117	-0.0087	-0.0066	-0.0174
Log-Log	Intercept	16.8741 *	8.4184	2.5350	26.6481 ***
Log-Log	Cost (ln)	-5.3862 ***	-4.6127 ***	-4.0046 ***	-4.7260 ***
Log-Log	Income (ln)	-0.8886	-0.1720	0.3366	-1.8927 **

Table C24: Conisbrough Huq regression results.

Model	Variable	Coef. (1)	Coef. (2)	Coef. (3)	Coef. (4)
Linear	Intercept	0.3617	0.2634	0.1814	0.4204
Linear	Cost	-0.0039 ***	-0.0029 ***	-0.002 ***	-0.0029 ***
Linear	Income (ln)	-0.0273	-0.0183	-0.0109	-0.0335
Log-Linear	Intercept	14.2216 **	6.9591	0.9519	19.3971 ***
Log-Linear	Cost	-0.3008 ***	-0.2222 ***	-0.154 ***	-0.2147 ***
Log-Linear	Income (ln)	-1.4936 **	-0.8314	-0.2866	-2.0431 ***
Linear-Log	Intercept	0.3386	0.198	0.0689	0.389
Linear-Log	Cost	-0.0748 ***	-0.0694 ***	-0.0643 ***	-0.0691 ***
Linear-Log	Income (ln)	-0.0115	0.002	0.0146	-0.0165
Log-Log	Intercept	16.8418 ***	8.8527	2.3433	21.568 ***
Log-Log	Cost (ln)	-5.0193 ***	-4.4943 ***	-4.0099 ***	-4.4259 ***
Log-Log	Income (ln)	-0.8912	-0.1706	0.4226	-1.4135 **

13.4 Appendix D

The following tables show the differences in the consumer surplus (CS), CS Per Capita and Recreation Vale for the 5 main sites of interest for both English Heritage and the mobile analytical company. As expected, as the opportunity cost increases, we see the consumer surplus increase. These results do show the significant variation that can occur by the decision on what the opportunity cost should be and raises significant methodological questions. The fluctuation between other studies in the sphere ranges from 0 to 150%, whereas in the main model we describe we use different data that utilises a real time emotion response to estimating the impact of travel on your happiness Krekel and Mackerron (2023).

Table D1: Audley End – opportunity cost 1.

Model	Metric	EH Value	Huq Value
Linear	CS	£246,314.03	£7,011.40
Linear	CS Per Capita	£1.11	£0.11
Linear	Ticket Revenue	£4,522,954	£1,419,846
Linear	Travel Cost	£845,029	£263,107
Linear	Total Opportunity Cost	£511,925	£149,358
Linear	Total Recreational Value	£6,126,222.03	£1,839,322.40
Log-Linear	CS	£346,635.27	£179,662.56
Log-Linear	CS Per Capita	£1.57	£2.83
Log-Linear	Ticket Revenue	£4,522,954	£1,419,846
Log-Linear	Travel Cost	£845,029	£263,107
Log-Linear	Total Opportunity Cost	£511,925	£149,358
Log-Linear	Total Recreational Value	£6,226,543.27	£2,011,973.56
Log-Log	CS	£375,576.04	£193,247.93
Log-Log	CS Per Capita	£1.70	£3.04
Log-Log	Ticket Revenue	£4,522,954	£1,419,846
Log-Log	Travel Cost	£845,029	£263,107
Log-Log	Total Opportunity Cost	£511,925	£149,358
Log-Log	Total Recreational Value	£6,255,484.04	£2,025,558.93
Linear-Log	CS	£221,113.36	£114.81
Linear-Log	CS Per Capita	£1.00	£0.00
Linear-Log	Ticket Revenue	£4,522,954	£1,419,846
Linear-Log	Travel Cost	£845,029	£263,107
Linear-Log	Total Opportunity Cost	£511,925	£149,358
Linear-Log	Total Recreational Value	£6,101,021.36	£1,832,425.81

Table D2: Audley End – opportunity cost 2.

Model	Metric	EH Value	Huq Value
Linear	CS	£351,358.28	£3,100.17
Linear	CS Per Capita	£1.59	£0.05
Linear	Ticket Revenue	£4,522,954	£1,419,846
Linear	Travel Cost	£845,029	£263,107
Linear	Total Opportunity Cost	£1,279,813	£373,395
Linear	Total Recreational Value	£6,999,154.28	£2,059,448.17
Log-Linear	CS	£531,759.49	£260,446.94
Log-Linear	CS Per Capita	£2.40	£4.10
Log-Linear	Ticket Revenue	£4,522,954	£1,419,846
Log-Linear	Travel Cost	£845,029	£263,107
Log-Linear	Total Opportunity Cost	£1,279,813	£373,395
Log-Linear	Total Recreational Value	£7,179,555.49	£2,316,794.94
Log-Log	CS	£591,957.18	£289,996.81
Log-Log	CS Per Capita	£2.67	£4.56
Log-Log	Ticket Revenue	£4,522,954	£1,419,846
Log-Log	Travel Cost	£845,029	£263,107
Log-Log	Total Opportunity Cost	£1,279,813	£373,395
Log-Log	Total Recreational Value	£7,239,753.18	£2,346,344.81
Linear-Log	CS	£306,969.66	£2,322.66
Linear-Log	CS Per Capita	£1.39	£0.04
Linear-Log	Ticket Revenue	£4,522,954	£1,419,846
Linear-Log	Travel Cost	£845,029	£263,107
Linear-Log	Total Opportunity Cost	£1,279,813	£373,395
Linear-Log	Total Recreational Value	£6,954,765.66	£2,058,670.66

Table D3: Audley End – opportunity cost 3.

Model	Metric	EH Value	Huq Value
Linear	CS	£536,911.51	£1,321.07
Linear	CS Per Capita	£2.42	£0.02
Linear	Ticket Revenue	£4,522,954	£1,419,846
Linear	Travel Cost	£845,029	£263,107
Linear	Total Opportunity Cost	£2,559,626	£746,790
Linear	Total Recreational Value	£8,464,520.51	£2,431,064.07
Log-Linear	CS	£843,661.13	£399,308.62
Log-Linear	CS Per Capita	£3.81	£6.28
Log-Linear	Ticket Revenue	£4,522,954	£1,419,846
Log-Linear	Travel Cost	£845,029	£263,107
Log-Linear	Total Opportunity Cost	£2,559,626	£746,790
Log-Linear	Total Recreational Value	£8,771,270.13	£2,829,051.62
Log-Log	CS	£970,937.67	£463,463.87
Log-Log	CS Per Capita	£4.38	£7.29
Log-Log	Ticket Revenue	£4,522,954	£1,419,846
Log-Log	Travel Cost	£845,029	£263,107
Log-Log	Total Opportunity Cost	£2,559,626	£746,790
Log-Log	Total Recreational Value	£8,898,546.67	£2,893,206.87
Linear-Log	CS	£448,037.08	£14,315.64
Linear-Log	CS Per Capita	£2.02	£0.23
Linear-Log	Ticket Revenue	£4,522,954	£1,419,846
Linear-Log	Travel Cost	£845,029	£263,107
Linear-Log	Total Opportunity Cost	£2,559,626	£746,790
Linear-Log	Total Recreational Value	£8,375,646.08	£2,444,058.64

Table D4: Belsay Hall – opportunity cost 1.

Model	Metric	EH Value	Huq Value
Linear	CS	£176,004.40	£61,439.61
Linear	CS Per Capita	£3.03	£1.53
Linear	Ticket Revenue	£870,945	£719,129
Linear	Travel Cost	£192,866	£128,195
Linear	Total Opportunity Cost	£94,316	£61,762
Linear	Total Recreational Value	£1,334,131.40	£970,525.61
Log-Linear	CS	£161,642.20	£129,842.08
Log-Linear	CS Per Capita	£2.78	£3.22
Log-Linear	Ticket Revenue	£870,945	£719,129
Log-Linear	Travel Cost	£192,866	£128,195
Log-Linear	Total Opportunity Cost	£94,316	£61,762
Log-Linear	Total Recreational Value	£1,319,769.20	£1,038,928.08
Log-Log	CS	£163,765.10	£136,026.52
Log-Log	CS Per Capita	£2.82	£3.38
Log-Log	Ticket Revenue	£870,945	£719,129
Log-Log	Travel Cost	£192,866	£128,195
Log-Log	Total Opportunity Cost	£94,316	£61,762
Log-Log	Total Recreational Value	£1,321,892.10	£1,045,112.52
Linear-Log	CS	£168,498.90	£54,556.11
Linear-Log	CS Per Capita	£2.90	£1.35
Linear-Log	Ticket Revenue	£870,945	£719,129
Linear-Log	Travel Cost	£192,866	£128,195
Linear-Log	Total Opportunity Cost	£94,316	£61,762
Linear-Log	Total Recreational Value	£1,326,625.90	£963,642.11

Table D5: Belsay Hall – opportunity cost 2.

Model	Metric	EH Value	Huq Value
Linear	CS	£239,051.00	£80,685.80
Linear	CS Per Capita	£4.11	£2.00
Linear	Ticket Revenue	£870,945	£719,129
Linear	Travel Cost	£192,866	£128,195
Linear	Total Opportunity Cost	£235,790	£154,404
Linear	Total Recreational Value	£1,538,652.00	£1,082,413.80
Log-Linear	CS	£226,683.20	£180,008.02
Log-Linear	CS Per Capita	£3.90	£4.47
Log-Linear	Ticket Revenue	£870,945	£719,129
Log-Linear	Travel Cost	£192,866	£128,195
Log-Linear	Total Opportunity Cost	£235,790	£154,404
Log-Linear	Total Recreational Value	£1,526,284.20	£1,181,736.02
Log-Log	CS	£231,104.90	£191,786.12
Log-Log	CS Per Capita	£3.98	£4.76
Log-Log	Ticket Revenue	£870,945	£719,129
Log-Log	Travel Cost	£192,866	£128,195
Log-Log	Total Opportunity Cost	£235,790	£154,404
Log-Log	Total Recreational Value	£1,530,705.90	£1,193,514.12
Linear-Log	CS	£226,379.30	£69,456.84
Linear-Log	CS Per Capita	£3.89	£1.72
Linear-Log	Ticket Revenue	£870,945	£719,129
Linear-Log	Travel Cost	£192,866	£128,195
Linear-Log	Total Opportunity Cost	£235,790	£154,404
Linear-Log	Total Recreational Value	£1,525,980.30	£1,071,184.84

Table D6: Belsay Hall – opportunity cost 3.

Model	Metric	EH Value	Huq Value
Linear	CS	£345,088.10	£113,600.29
Linear	CS Per Capita	£5.94	£2.82
Linear	Ticket Revenue	£870,945	£719,129
Linear	Travel Cost	£192,866	£128,195
Linear	Total Opportunity Cost	£471,580	£308,809
Linear	Total Recreational Value	£1,880,479.10	£1,269,733.29
Log-Linear	CS	£335,805.60	£264,162.85
Log-Linear	CS Per Capita	£5.78	£6.56
Log-Linear	Ticket Revenue	£870,945	£719,129
Log-Linear	Travel Cost	£192,866	£128,195
Log-Linear	Total Opportunity Cost	£471,580	£308,809
Log-Linear	Total Recreational Value	£1,871,196.60	£1,420,295.85
Log-Log	CS	£345,831.10	£288,739.36
Log-Log	CS Per Capita	£5.95	£7.17
Log-Log	Ticket Revenue	£870,945	£719,129
Log-Log	Travel Cost	£192,866	£128,195
Log-Log	Total Opportunity Cost	£471,580	£308,809
Log-Log	Total Recreational Value	£1,881,222.10	£1,444,872.36
Linear-Log	CS	£322,418.30	£94,659.07
Linear-Log	CS Per Capita	£5.55	£2.35
Linear-Log	Ticket Revenue	£870,945	£719,129
Linear-Log	Travel Cost	£192,866	£128,195
Linear-Log	Total Opportunity Cost	£471,580	£308,809
Linear-Log	Total Recreational Value	£1,857,809.30	£1,250,792.07

Table D7: Eltham Palace – opportunity cost 1.

Model	Metric	EH Value	Huq Value
Linear	CS	£201,662.72	£75,199.70
Linear	CS Per Capita	£2.40	£2.30
Linear	Ticket Revenue	£2,257,839	£890,557
Linear	Travel Cost	£159,290	£80,790
Linear	Total Opportunity Cost	£139,384	£59,832
Linear	Total Recreational Value	£2,758,175.72	£1,106,378.70
Log-Linear	CS	£183,391.32	£102,326.28
Log-Linear	CS Per Capita	£2.18	£3.13
Log-Linear	Ticket Revenue	£2,257,839	£890,557
Log-Linear	Travel Cost	£159,290	£80,790
Log-Linear	Total Opportunity Cost	£139,384	£59,832
Log-Linear	Total Recreational Value	£2,739,904.32	£1,133,505.28
Log-Log	CS	£197,040.88	£111,238.30
Log-Log	CS Per Capita	£2.34	£3.40
Log-Log	Ticket Revenue	£2,257,839	£890,557
Log-Log	Travel Cost	£159,290	£80,790
Log-Log	Total Opportunity Cost	£139,384	£59,832
Log-Log	Total Recreational Value	£2,753,553.88	£1,142,417.30
Linear-Log	CS	£187,485.66	£71,073.00
Linear-Log	CS Per Capita	£2.23	£2.17
Linear-Log	Ticket Revenue	£2,257,839	£890,557
Linear-Log	Travel Cost	£159,290	£80,790
Linear-Log	Total Opportunity Cost	£139,384	£59,832
Linear-Log	Total Recreational Value	£2,743,998.66	£1,102,252.00

Table D8: Eltham Palace – opportunity cost 2.

Model	Metric	EH Value	Huq Value
Linear	CS	£262,745.79	£93,355.01
Linear	CS Per Capita	£3.13	£2.85
Linear	Ticket Revenue	£2,257,839	£890,557
Linear	Travel Cost	£159,290	£80,790
Linear	Total Opportunity Cost	£348,459	£149,579
Linear	Total Recreational Value	£3,028,333.79	£1,214,281.01
Log-Linear	CS	£263,430.84	£143,196.61
Log-Linear	CS Per Capita	£3.13	£4.37
Log-Linear	Ticket Revenue	£2,257,839	£890,557
Log-Linear	Travel Cost	£159,290	£80,790
Log-Linear	Total Opportunity Cost	£348,459	£149,579
Log-Linear	Total Recreational Value	£3,029,018.84	£1,264,122.61
Log-Log	CS	£291,004.90	£159,771.43
Log-Log	CS Per Capita	£3.46	£4.88
Log-Log	Ticket Revenue	£2,257,839	£890,557
Log-Log	Travel Cost	£159,290	£80,790
Log-Log	Total Opportunity Cost	£348,459	£149,579
Log-Log	Total Recreational Value	£3,056,592.90	£1,280,697.43
Linear-Log	CS	£240,401.98	£87,334.93
Linear-Log	CS Per Capita	£2.86	£2.67
Linear-Log	Ticket Revenue	£2,257,839	£890,557
Linear-Log	Travel Cost	£159,290	£80,790
Linear-Log	Total Opportunity Cost	£348,459	£149,579
Linear-Log	Total Recreational Value	£3,005,989.98	£1,208,260.93

Table D9: Eltham Palace – opportunity cost 3.

Model	Metric	EH Value	Huq Value
Linear	CS	£373,507.25	£128,543.48
Linear	CS Per Capita	£4.44	£3.93
Linear	Ticket Revenue	£2,257,839	£890,557
Linear	Travel Cost	£159,290	£80,790
Linear	Total Opportunity Cost	£696,919	£299,158
Linear	Total Recreational Value	£3,487,555.25	£1,399,048.48
Log-Linear	CS	£401,499.86	£214,136.40
Log-Linear	CS Per Capita	£4.78	£6.54
Log-Linear	Ticket Revenue	£2,257,839	£890,557
Log-Linear	Travel Cost	£159,290	£80,790
Log-Linear	Total Opportunity Cost	£696,919	£299,158
Log-Linear	Total Recreational Value	£3,515,547.86	£1,484,641.40
Log-Log	CS	£460,499.77	£248,621.17
Log-Log	CS Per Capita	£5.48	£7.59
Log-Log	Ticket Revenue	£2,257,839	£890,557
Log-Log	Travel Cost	£159,290	£80,790
Log-Log	Total Opportunity Cost	£696,919	£299,158
Log-Log	Total Recreational Value	£3,574,547.77	£1,519,126.17
Linear-Log	CS	£335,853.22	£119,036.31
Linear-Log	CS Per Capita	£4.00	£3.64
Linear-Log	Ticket Revenue	£2,257,839	£890,557
Linear-Log	Travel Cost	£159,290	£80,790
Linear-Log	Total Opportunity Cost	£696,919	£299,158
Linear-Log	Total Recreational Value	£3,449,901.22	£1,389,541.31

Table D10: Mount Grace Priory – opportunity cost 1.

Model	Metric	EH Value	Huq Value
Linear	CS	£38,688.37	£12,474.31
Linear	CS Per Capita	£1.65	£1.80
Linear	Ticket Revenue	£402,007	£122,032
Linear	Travel Cost	£125,471	£40,949
Linear	Total Opportunity Cost	£47,868	£14,109
Linear	Total Recreational Value	£614,034.37	£189,564.31
Log-Linear	CS	£78,638.75	£27,307.70
Log-Linear	CS Per Capita	£3.35	£3.95
Log-Linear	Ticket Revenue	£402,007	£122,032
Log-Linear	Travel Cost	£125,471	£40,949
Log-Linear	Total Opportunity Cost	£47,868	£14,109
Log-Linear	Total Recreational Value	£653,984.75	£204,397.70
Log-Log	CS	£85,957.07	£32,580.81
Log-Log	CS Per Capita	£3.66	£4.71
Log-Log	Ticket Revenue	£402,007	£122,032
Log-Log	Travel Cost	£125,471	£40,949
Log-Log	Total Opportunity Cost	£47,868	£14,109
Log-Log	Total Recreational Value	£661,303.07	£209,670.81
Linear-Log	CS	£37,411.63	£12,308.67
Linear-Log	CS Per Capita	£1.59	£1.78
Linear-Log	Ticket Revenue	£402,007	£122,032
Linear-Log	Travel Cost	£125,471	£40,949
Linear-Log	Total Opportunity Cost	£47,868	£14,109
Linear-Log	Total Recreational Value	£612,757.63	£189,398.67

Table D11: Mount Grace Priory – opportunity cost 2.

Model	Metric	EH Value	Huq Value
Linear	CS	£51,840.16	£16,397.43
Linear	CS Per Capita	£2.21	£2.37
Linear	Ticket Revenue	£402,007	£122,032
Linear	Travel Cost	£125,471	£40,949
Linear	Total Opportunity Cost	£119,671	£35,273
Linear	Total Recreational Value	£698,989.16	£214,651.43
Log-Linear	CS	£108,962.78	£36,848.51
Log-Linear	CS Per Capita	£4.64	£5.33
Log-Linear	Ticket Revenue	£402,007	£122,032
Log-Linear	Travel Cost	£125,471	£40,949
Log-Linear	Total Opportunity Cost	£119,671	£35,273
Log-Linear	Total Recreational Value	£756,111.78	£235,102.51
Log-Log	CS	£121,997.72	£45,690.19
Log-Log	CS Per Capita	£5.19	£6.61
Log-Log	Ticket Revenue	£402,007	£122,032
Log-Log	Travel Cost	£125,471	£40,949
Log-Log	Total Opportunity Cost	£119,671	£35,273
Log-Log	Total Recreational Value	£769,146.72	£243,944.19
Linear-Log	CS	£49,958.06	£16,234.73
Linear-Log	CS Per Capita	£2.13	£2.35
Linear-Log	Ticket Revenue	£402,007	£122,032
Linear-Log	Travel Cost	£125,471	£40,949
Linear-Log	Total Opportunity Cost	£119,671	£35,273
Linear-Log	Total Recreational Value	£697,107.06	£214,488.73

Table D12: Mount Grace Priory – opportunity cost 3.

Model	Metric	EH Value	Huq Value
Linear	CS	£74,546.93	£23,209.02
Linear	CS Per Capita	£3.17	£3.36
Linear	Ticket Revenue	£402,007	£122,032
Linear	Travel Cost	£125,471	£40,949
Linear	Total Opportunity Cost	£239,341	£70,546
Linear	Total Recreational Value	£841,365.93	£256,736.02
Log-Linear	CS	£159,964.76	£53,007.72
Log-Linear	CS Per Capita	£6.81	£7.67
Log-Linear	Ticket Revenue	£402,007	£122,032
Log-Linear	Travel Cost	£125,471	£40,949
Log-Linear	Total Opportunity Cost	£239,341	£70,546
Log-Linear	Total Recreational Value	£926,783.76	£286,534.72
Log-Log	CS	£185,205.41	£69,103.42
Log-Log	CS Per Capita	£7.88	£9.99
Log-Log	Ticket Revenue	£402,007	£122,032
Log-Log	Travel Cost	£125,471	£40,949
Log-Log	Total Opportunity Cost	£239,341	£70,546
Log-Log	Total Recreational Value	£952,024.41	£302,630.42
Linear-Log	CS	£71,327.73	£23,014.03
Linear-Log	CS Per Capita	£3.04	£3.33
Linear-Log	Ticket Revenue	£402,007	£122,032
Linear-Log	Travel Cost	£125,471	£40,949
Linear-Log	Total Opportunity Cost	£239,341	£70,546
Linear-Log	Total Recreational Value	£838,146.73	£256,541.03

Table D13: Stokesay Castle – opportunity cost 1.

Model	Metric	EH Value	Huq Value
Linear	CS	£20,629.66	£1,280.11
Linear	CS Per Capita	£2.13	£0.87
Linear	Ticket Revenue	£280,243	£24,048
Linear	Travel Cost	£65,370	£6,998
Linear	Total Opportunity Cost	£34,059	£3,487
Linear	Total Recreational Value	£400,301.66	£35,813.11
Log-Linear	CS	£43,309.16	£5,035.64
Log-Linear	CS Per Capita	£4.46	£3.41
Log-Linear	Ticket Revenue	£280,243	£24,048
Log-Linear	Travel Cost	£65,370	£6,998
Log-Linear	Total Opportunity Cost	£34,059	£3,487
Log-Linear	Total Recreational Value	£422,981.16	£39,568.64
Log-Log	CS	£55,386.13	£3.41
Log-Log	CS Per Capita	£5.71	£39,567.85
Log-Log	Ticket Revenue	£280,243	£24,048
Log-Log	Travel Cost	£65,370	£6,998
Log-Log	Total Opportunity Cost	£34,059	£3,487
Log-Log	Total Recreational Value	£435,058.13	£40,306.06
Linear-Log	CS	£20,161.05	£567.09
Linear-Log	CS Per Capita	£2.08	£0.38
Linear-Log	Ticket Revenue	£280,243	£24,048
Linear-Log	Travel Cost	£65,370	£6,998
Linear-Log	Total Opportunity Cost	£34,059	£3,487
Linear-Log	Total Recreational Value	£399,833.05	£35,100.09

Table D14: Stokesay Castle – opportunity cost 2.

Model	Metric	EH Value	Huq Value
Linear	CS	£28,780.34	£1,425.13
Linear	CS Per Capita	£2.97	£0.97
Linear	Ticket Revenue	£280,243	£24,048
Linear	Travel Cost	£65,370	£6,998
Linear	Total Opportunity Cost	£85,146	£8,716
Linear	Total Recreational Value	£459,539.34	£41,187.13
Log-Linear	CS	£62,692.23	£7,130.69
Log-Linear	CS Per Capita	£6.46	£4.83
Log-Linear	Ticket Revenue	£280,243	£24,048
Log-Linear	Travel Cost	£65,370	£6,998
Log-Linear	Total Opportunity Cost	£85,146	£8,716
Log-Linear	Total Recreational Value	£493,451.23	£46,892.69
Log-Log	CS	£85,346.62	£8,569.33
Log-Log	CS Per Capita	£8.79	£5.80
Log-Log	Ticket Revenue	£280,243	£24,048
Log-Log	Travel Cost	£65,370	£6,998
Log-Log	Total Opportunity Cost	£85,146	£8,716
Log-Log	Total Recreational Value	£516,105.62	£48,331.33
Linear-Log	CS	£28,259.80	£452.62
Linear-Log	CS Per Capita	£2.91	£0.31
Linear-Log	Ticket Revenue	£280,243	£24,048
Linear-Log	Travel Cost	£65,370	£6,998
Linear-Log	Total Opportunity Cost	£85,146	£8,716
Linear-Log	Total Recreational Value	£459,018.80	£40,214.62

Table D15: Stokesay Castle – opportunity cost 3.

Model	Metric	EH Value	Huq Value
Linear	CS	£42,773.92	£1,755.22
Linear	CS Per Capita	£4.41	£1.19
Linear	Ticket Revenue	£280,243	£24,048
Linear	Travel Cost	£65,370	£6,998
Linear	Total Opportunity Cost	£170,293	£17,433
Linear	Total Recreational Value	£558,679.92	£50,234.22
Log-Linear	CS	£95,499.46	£10,671.95
Log-Linear	CS Per Capita	£9.84	£7.23
Log-Linear	Ticket Revenue	£280,243	£24,048
Log-Linear	Travel Cost	£65,370	£6,998
Log-Linear	Total Opportunity Cost	£170,293	£17,433
Log-Linear	Total Recreational Value	£611,405.46	£59,150.95
Log-Log	CS	£139,567.14	£13,556.63
Log-Log	CS Per Capita	£14.38	£9.18
Log-Log	Ticket Revenue	£280,243	£24,048
Log-Log	Travel Cost	£65,370	£6,998
Log-Log	Total Opportunity Cost	£170,293	£17,433
Log-Log	Total Recreational Value	£655,473.14	£62,035.63
Linear-Log	CS	£42,060.54	£343.03
Linear-Log	CS Per Capita	£4.33	£0.23
Linear-Log	Ticket Revenue	£280,243	£24,048
Linear-Log	Travel Cost	£65,370	£6,998
Linear-Log	Total Opportunity Cost	£170,293	£17,433
Linear-Log	Total Recreational Value	£557,966.54	£48,822.03

13.5 Appendix E

These images show the old and new polygons for the sites that were adjusted as discussed in Section 8.2 and Section 8.3. The orange area is the old polygon and the pink area represents what was added in the new polygons. We see that in most cases, the size of the polygon was increased and designed to include the car park.

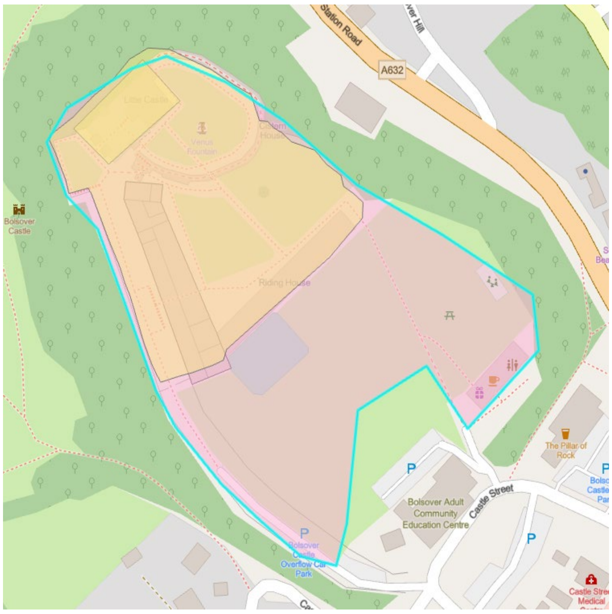


Figure E1: Bolsover Castle.

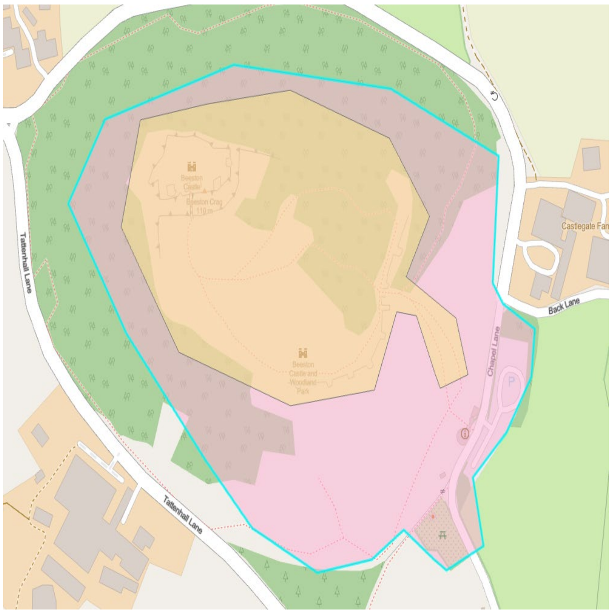


Figure E2: Beeston Castle

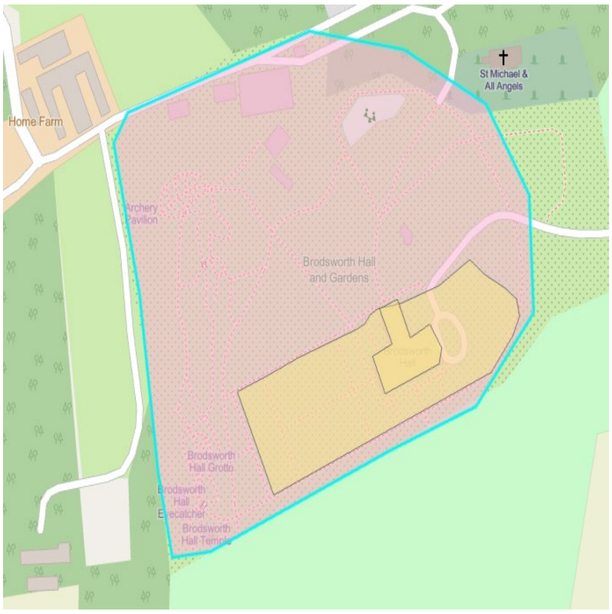


Figure E3: Brodsworth Hall and Gardens.

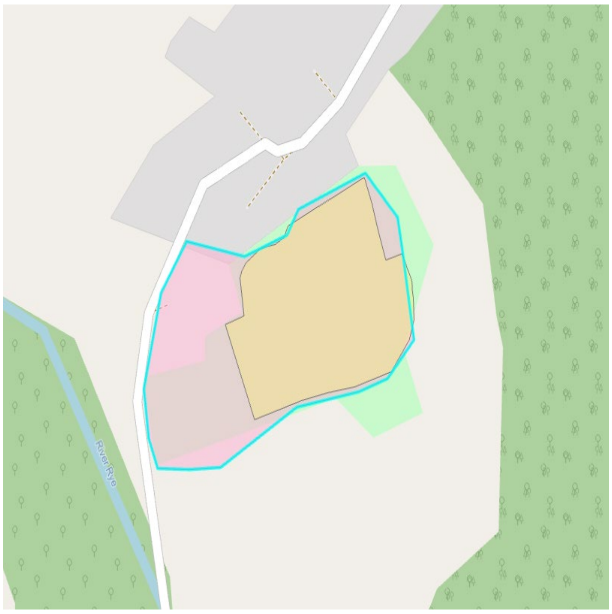


Figure E4: Rievaulx Abbey.

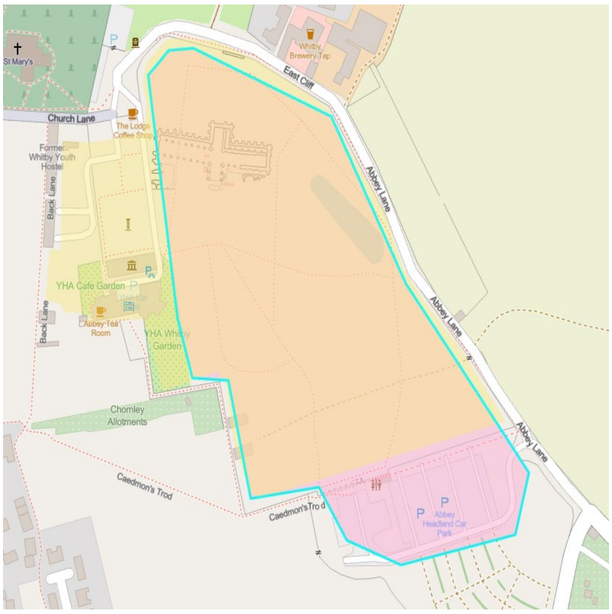


Figure 5: Whitby Abbey.

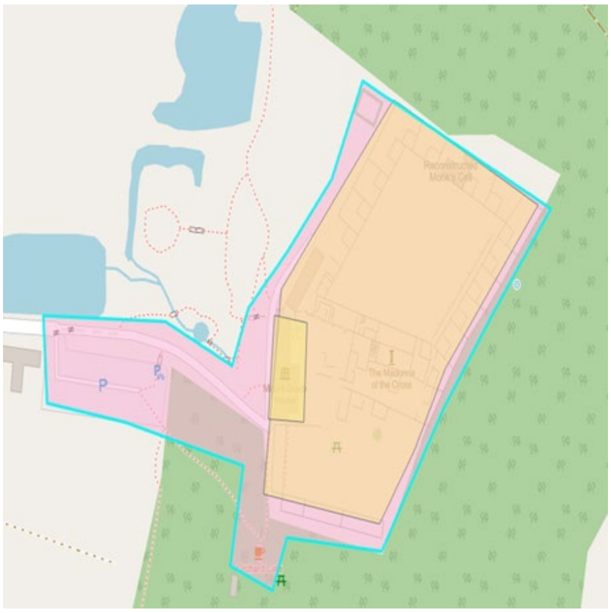


Figure 6: Mount Grace Priory.

Figure 7: Stokesay Castle.

13.6 Appendix F

This proceeds through the estimation of the NPV, PI, and BCR as described in Section 8.

13.6.1 Scenario 1

In this scenario, the historic attraction operates with a Profitability Index (PI) of 0.9, where benefits derive solely from admission fees, while costs are operational. Without factoring in consumer surplus, the site requires a subsidy to cover its operating expenses over the 10-year period.

Assumptions:

- Average admission fee per visitors = £12.38
- Number of visitors = 58,000
- Consumer surplus per capita: £4.95
- Average annual operation costs of £800,000

$$\text{Discounted Benefits} = \sum_{1}^{10} (58{,}000 * 12.38 * DF_t) = £6{,}125{,}027$$

$$\text{Discounted Costs} = \sum_{1}^{10} (£800{,}000 * DF_t) = £6{,}824{,}162$$

Therefore, giving a NPV over 10 years:

$$NPV = 6{,}125{,}027 - 6{,}824{,}162 = £699{,}135$$

$$Profability\ Index\ (PI) = \frac{£6{,}125{,}027}{£6{,}824{,}162} = 0.9$$

Estimate for Discounted Consumer Surplus:

$$\text{Discounted Consumer Surplus} = \sum_{1}^{10} (58{,}000 * £4.95 * DF_t) = £2{,}499{,}021$$

NPV with consumer surplus:

$$NPV = (£6{,}824{,}162 + 2{,}499{,}021) \; - \; £6{,}824{,}162 = £1{,}749{,}886$$

This shows a net present value now of £1,749,886

$$Recreational\ Value\ Index\ (RVI) = \frac{£6{,}824{,}162 + 2{,}499{,}021}{£1{,}749{,}886} = 1.26$$

And shows a Recreational Value Index of 1.26. The inclusion of the consumer surplus in the analysis shows that the site has significant non-market value, justifying continued support to preserve its cultural and historical significance, and additional funding may wish to be made available to cover the operational shortfall.

13.6.2 Scenario 2

This scenario demonstrates the impact of a repair and maintenance cost of £2,138,038 spread evenly over a ten-year window and on an overwise profitable site. Due to discounting, the total additional cost of this is £1,823,789 at year 1 of the window.

Assumptions:

- Number of visitors = 58,000
- Average admission fee per visitors = £12.38
- Consumer surplus per capita: £4.95
- Average annual operation costs of £704,000
- repair and maintenance cost of £2,138,038

$$\text{Discounted Market Benefits } = \sum_{1}^{10}(58{,}000 * 12.38 * DF_t) = £6{,}125{,}027$$

$$\text{Costs } = \sum_{1}^{10}(Annual\ costs) = £6{,}005{,}263$$

Therefore, NPV and PI before repair and maintenance is equal to

$$NPV = 6{,}125{,}027 \; - \; £6{,}005{,}263 = £119{,}764$$

However, an additional repair and maintenance cost over 10 years can cause a negative NPV over the following 10 years on an overwise profitable site.

$$\text{Costs} = \sum_{1}^{10}\left((Annual\ costs + R\&M) * DF_t\right) = £7{,}829{,}053$$

$$NPV = £6{,}125{,}027 - (£6{,}005{,}263 + £1{,}823{,}789) = -£1{,}704{,}026$$

This also reduce the RVI down to below 1 for this given period.

$$Profitability\ Index\ (PI) = \frac{£6{,}125{,}027}{£6{,}005{,}263 + £1{,}823{,}789} = 0.78$$

However, with the inclusion of the consumer surplus:

$$\text{Discounted Recreational Value} = \sum_{1}^{10}(58{,}000 * £4.95 * DF_t) = £2{,}499{,}021$$

$$NPV = (£6{,}125{,}027 + £2{,}449{,}021) - (£6{,}005{,}263 + £1{,}823{,}789) = £744{,}996$$

$$Recreational\ Value\ Index\ (RVI) = \frac{£6{,}125{,}027 + £2{,}449{,}021}{£6{,}005{,}263 + £1{,}823{,}789} = 1.1$$

Thus, there is a risk that the need for repair and maintenance could make the historic attraction site insolvent, risking the loss of heritage. Without the consideration of the consumer surplus, the NPV would be negative for the following 10 years, and the RVI would be below 1 and may not warrant intervention, however when considering the consumer surplus this is above 1 and would warrant further investment.

13.6.3 Scenario 3

This scenario demonstrates the impact of a repair and maintenance cost of £2,138,038 on the BCR on an overwise profitable site, alongside a £2.5 million investment to improve the visitor attraction site and subsequently increase the number of annual visitors.

Assumptions:

- Number of current visitors = 58,000
- Number of additional visitors = 23,000
- Average admission fee per visitors = £12.38
- Consumer surplus per capita: £4.95
- Average annual operation costs of £704,000
- Repair and maintenance cost of £2,138,038, split evenly over 10 years
- £2.5 million investment to improve the visitor experience

Current benefits assuming no additional investment and presence of one time cost:

$$\text{Discounted Market Benefits (no investment)} = \sum_{1}^{10}(58{,}000 * 12.38 * DF_t) = £6{,}125{,}027$$

Benefits assuming that investment occurs and increase the number of visitors by 23,000.

$$\text{Discounted Market Benefits (Investment)} = \sum_{1}^{10}(81{,}000 * 12.38 * DF_t) = £8{,}553{,}916$$

Costs over a 10-year period, annual costs are not considered as part of the requirement for additional funding, however one time cost and investment are considered and therefore discounted.

$$\text{Costs} = \sum_{1}^{10}(Annual\ costs + R\&M + Invesment *\ DF_t) = £9{,}961{,}603$$

Therefore, the addition of these costs would reduce the net present value over the next 10 years to be negative.

$$NPV = £8{,}553{,}916 - (£6{,}005{,}263 + £1{,}823{,}789 + £2{,}132{,}550) = -£1{,}407{,}686$$

Without consideration of the consumer surplus, the PI is below that of 1.

$$Profitability\ Index = \frac{£8,553,916}{£6,005,263 + £1,823,789 + £2,132,550} = 0.86$$

However, with the inclusion of the additionality from the non-market benefits there is a £3.4 million uplift in the value of the site over the 10 year period.

$$\text{Discounted Recreational Value } = \sum_{1}^{10}(81,000 * £4.95 * DF_t) = £3,420,184$$

This results in a positive Net Present Value over the same 10-year period

$$NPV = (£8,553,956 + £3,420,185)\ - (£6,005,263 + £1,823,789 + £2,132,550) = £2,012,498$$

The RVI therefore returns to above 1

$$Recreational\ Value\ Index\ (RVI) = \frac{£8,553,956 + £3,420,185}{£6,005,263 + £1,823,789 + £2,132,550} = 1.20$$

With the inclusion of consumer surplus, we achieve a positive PNV and RVI of above 1.20.

However, if the non-market benefits measured through consumer surplus also increase due to intervention to £6.50, then the following would apply.

$$\text{Discounted Consumer Surplus } = \sum_{1}^{10}(81,000 * £6.50 * DF_t) = £4,491,152$$

$$NPV = (£8,553,956 + £4,491,152)\ - (£6,005,263 + £1,823,789 + £2,132,550) = £3,084,465$$

$$Recreational\ Value\ Index\ (RVI) = \frac{£8,553,956 + £4,491,152}{£6,005,263 + £1,823,789 + £2,132,550} = 1.31$$

This can demonstrate the significant impact that the inclusion of the non-market benefits can make on a decision-making, making a stronger business case for support to the heritage industry.

13.6.4 Scenario 4

This scenario demonstrates the impact of a £2.5 million investment to improve the visitor attraction site – to increase the number of visitors annually, and in the latter case increase in the consumer surplus value. Instead of the prementioned cases where we discussed Profitability Index, Net Present Value and Recreational Value Index, this uses a more classical approach considering just the impact the investment has, therefore we use a Benefit Cost Ratio (BCR). This would be more useful in the case of a business case just seeking the investment.

Assumptions:

- Number of current visitors = 58,000
- Number of additional visitors = 23,000
- Average admission fee per visitors = £12.38
- Consumer surplus per capita: £4.95
- Average annual operation costs of £600,000
- £2.5 million investment to improve the visitor experience

Benefits of the investment are considered over a 10-year span, increasing the number of visitors annually by 23,000.

$$\text{Discounted Benefits (Investment)} = \sum_{1}^{10}(23{,}000 * 12.38 * DF_t) = £2{,}428{,}890$$

Discounted cost of the investment is considered over the same period, assuming equal spend per year.

$$\text{Costs} = \sum_{1}^{10}(Invesment * DF) = £2{,}132{,}550$$

BCR is shown to be above 1, but not significantly.

$$BCR = \frac{£2{,}428{,}890}{£2{,}132{,}551} = 1.13$$

However, when considering the total recreational value including the consumer surplus, the BCR improves to 1.59

$$\text{Discounted Consumer Surplus Benefits (Investment)} = \sum_{1}^{10}(23{,}000 * (12.38 + £4.95) * DF_t) = £3{,}400{,}053$$

$$BCR = \frac{£3{,}400{,}053}{£2{,}132{,}551} = 1.59$$

It is however also feasible that the improvement of the site also increases the consumer surplus per capita. This could be estimated with the stated methodology above for comparative sites, who have undergone an investment. An increase from £4.95 to £6.50 would result in the following

$$\text{Discounted Consumer Surplus Benefits (Investment)} = \sum_{1}^{10}\Big(\big(23{,}000 * (12.38 + £6.50)\big) + \big(58{,}000 * (£6.50 - £4.95)\big) * DF_t\Big) = £4{,}655{,}553$$

$$BCR = \frac{£4{,}655{,}553}{£2{,}132{,}551} = 2.18$$

The BCR becomes 2.18, showing a strong justification for investment.

13.7 Appendix G

Example consumer surplus calculations, adapted from Chotikapanich and Griffiths, (1998).

13.7.1 Example: Linear Model

The post-estimation relationship is given as:

$$\widehat{y_i} = \widehat{\beta_0} + \widehat{\beta_1}C_i + \widehat{\beta_2}I_i.$$

Each zone responds uniformly to a change, p, in price:

$$\widehat{y_i}(p) = \widehat{\beta_0} + \widehat{\beta_1}(C_i + p) + \widehat{\beta_2}I_i.$$

The aggregate estimate impact on total visitors is:

$$\widehat{Q(p)} = \sum_i^m N_i\,\widehat{y_i(p)} = \sum_i^m N_i\left(\widehat{\beta_0} + \widehat{\beta_1}(C_i + p) + \widehat{\beta_2}I_i\right)$$

From this equation, one can define the price increase, p^*, for which the site has no visitors ($\hat{Q}(p^*) = 0$). Such that

$$p^* = -\frac{\sum_i^m N_i\left(\widehat{\beta_0} + \widehat{\beta_1}\mathrm{C_i} + \widehat{\beta_2}I_i\right)}{\sum_i^m N_i\widehat{\beta_1}}.$$

Giving the following estimated consumer surplus:

$$\begin{aligned}
\widehat{CS} &= \int_0^{p^*}\widehat{Q(p)}dp \\
&= \int_0^{p^*}\sum_i^m N_i\left(\widehat{\beta_0} + \widehat{\beta_1}(C_i + p) + \widehat{\beta_2}I_i\right)dp \\
&= \left[\sum_i^m N_i\left(\widehat{\beta_0} + \widehat{\beta_1}\mathrm{C_i} + \widehat{\beta_2}I_i\right)p + \left(\sum_i^m N_i\,\widehat{\beta_1}\right)\frac{p^2}{2}\right]_{p=0}^{p=p^*} \\
&= \sum_i^m N_i\left(\widehat{\beta_0} + \widehat{\beta_1}\mathrm{C_i} + \widehat{\beta_2}I_i\right)p^* + \left(\sum_i^m N_i\,\widehat{\beta_1}\right)\frac{p^{*2}}{2}.
\end{aligned}$$

13.7.2 Example: Linear-log model

The post-estimation relationship is given as:

$$\widehat{y_i} = \widehat{\beta_0} + \widehat{\beta_1}\, log\, C_i + \widehat{\beta_2} I_i.$$

Each zone responds to a uniform change in price (p) such that:

$$\widehat{y_i}(p) = \widehat{\beta_0} + \widehat{\beta_1}\, log(C_i + p) + \widehat{\beta_2} I_i.$$

Giving an aggregate demand relationship of:

$$\hat{Q}(p) = \sum_{i=1}^{m} N_i\left(\widehat{\beta_0} + \widehat{\beta_1}\, log(C_i + p) + \widehat{\beta_2} I_i\right).$$

As above, we need to find the p^*such that $\hat{Q}(p^*) = 0$. Unlike above, the roots to the above equation must be found numerically. In this paper, roots were found using the Newton-Rhapson method. With the knowledge that a solution to $\hat{Q}(p^*) = 0$ cannot be found by hand, the Newton-Rhapson method begins by making a 'guess' of a potential solution. Then, as it iterates through the algorithm it makes closer and closer approximations to the true solution. Finally, the algorithm stops when the function is close enough to zero. The algorithm works by utilising our differentiable demand function to make an accurate approximation of where this function crosses the x-axis. The remaining steps follow as below:

$$\begin{aligned}
\widehat{CS} &= \int_0^{p^*} \hat{Q}(p)dp \\
&= \int_0^{p^*} \sum_{i=1}^{m} N_i\left(\widehat{\beta_0} + \widehat{\beta_1}\, log(C_i + p) + \widehat{\beta_2} I_i\right) \\
&= \left[\sum_{i=1}^{m} N_i\left(\widehat{\beta_0} + \widehat{\beta_1} I_i\right)p + \sum_{i=1}^{m} \frac{\widehat{\beta_1}}{C_i + p}\right]_{p=0}^{p=p^*} \\
&= \sum_{i=1}^{m} N_i\left(\widehat{\beta_0} + \widehat{\beta_1} I_i\right)p^* + \sum_{i=1}^{m} \frac{\widehat{\beta_1}}{C_i + p^*} - \sum_{i=1}^{m} \frac{\widehat{\beta_1}}{C_i}.
\end{aligned}$$

13.7.3 Example: Log-log model

The post-estimation relationship is given as:

$$log\,\widehat{y_i} = \widehat{\beta_0} + \widehat{\beta_1}\,log\,C_i + \widehat{\beta_2}I_i.$$

This can be rearranged such that:

$$\widehat{y_i} = exp\left(\widehat{\beta_0} + \widehat{\beta_2}I_i\right)(C_i)^{\widehat{\beta_1}}.$$

Each zone responds to a uniform change in price (p) such that:

$$\widehat{y_i}(p) = exp\left(\widehat{\beta_0} + \widehat{\beta_2}I_i\right)(C_i + p)^{\widehat{\beta_1}}.$$

Giving an aggregate demand relationship of

$$\hat{Q}(p) = \sum_{i=1}^{m} N_i\left(exp\left(\widehat{\beta_0} + \widehat{\beta_2}I_i\right)(C_i + p)^{\widehat{\beta_1}}\right).$$

If we assume that $\widehat{\beta_1} < -1$ then $\hat{Q}(p) \to 0$ as $p \to \infty$. This gives us an aggregate consumer surplus equation of

$$\widehat{CS} = \lim_{p^* \to \infty} \int_0^{p^*} \sum_{i=1}^{m} N_i\left(exp\left(\widehat{\beta_0} + \widehat{\beta_2}I_i\right)(C_i + p)^{\widehat{\beta_1}}\right) dp$$

$$= \lim_{p^* \to \infty} \left[\frac{1}{\widehat{\beta_1} + 1} \sum_{i=1}^{m} N_i\left(exp\left(\widehat{\beta_0} + \widehat{\beta_2}I_i\right)(C_i + p)^{\widehat{\beta_1 + 1}}\right)\right]_0^{p^*}.$$

Again, since $\widehat{\beta_1} < -1$ then the upper limit of the integral goes to zero and

$$\widehat{CS} = -\frac{1}{\widehat{\beta_1} + 1} \sum_{i=1}^{m} N_i\left(exp\left(\widehat{\beta_0} + \widehat{\beta_2}I_i\right)(C_i)^{\widehat{\beta_1 + 1}}\right).$$

13.7.4 Example: Log-linear model

The post-estimation relationship is given as:

$$\log \widehat{y_i} = \widehat{\beta_0} + \widehat{\beta_1} C_i + \widehat{\beta_2} I_i.$$

This can be rearranged such that:

$$\widehat{y_i} = exp\left(\widehat{\beta_0} + \widehat{\beta_1} C_i + \widehat{\beta_2} I_i\right).$$

Each zone responds to uniform change in price, p, such that:

$$\widehat{y_i}(p) = exp\left(\widehat{\beta_0} + \widehat{\beta_1}(C_i + p) + \widehat{\beta_2} I_i\right).$$

Giving an aggregate demand relationship of

$$\hat{Q}(p) = \sum_{i=1}^{m} N_i\left(exp\left(\widehat{\beta_0} + \widehat{\beta_1}(C_i + p) + \widehat{\beta_2} I_i\right)\right).$$

Since $\widehat{\beta_1} < 0$ then $\hat{Q} \to 0$ as $p \to \infty$. This gives us an aggregate consumer surplus equation of

$$\widehat{CS} = \lim_{p^* \to \infty} \int_0^{p^*} \sum_{i=1}^{m} N_i\left(exp\left(\widehat{\beta_0} + \widehat{\beta_1}(C_i + p) + \widehat{\beta_2} I_i\right)\right) dp.$$

Evaluating the integral gives

$$\widehat{CS} = \lim_{p^* \to \infty} \left[\frac{\sum_{i=1}^{m} N_i\left(exp\left(\widehat{\beta_0} + \widehat{\beta_1}(C_i + p) + \widehat{\beta_2} I_i\right)\right)}{\widehat{\beta_1}}\right]_0^{p^*}.$$

The upper limit of the integral goes to zero giving

$$\widehat{CS} = -\frac{\sum_{i=1}^{m} N_i\left(exp\left(\widehat{\beta_0} + \widehat{\beta_1} C_i + \widehat{\beta_2} I_i\right)\right)}{\widehat{\beta_1}}.$$

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