THESIS

VALUING VISITOR EXPERIENCE: A STATED PREFERENCE ANALYSIS OF CONGESTION IN KATMAI NATIONAL PARK

Submitted by

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ABSTRACT

VALUING VISITOR EXPERIENCE: A STATED PREFERENCE ANALYSIS OF CONGESTION IN KATMAI NATIONAL PARK

Katmai National Park is home to more than 2,000 brown bears, offering unique wildlife viewing opportunities for visitors. Brooks Camp, the most well-known and accessible recreation site in Katmai, has seen a 139% increase in visitation since webcams were installed in 2012 around the site to livestream bear activity on explore.org. This dramatic increase has created management challenges related to visitor experience and resource protection. Therefore, understanding visitor perceptions of crowding and preferences for management alternatives is becoming increasingly important for park management.

This study presents findings from a visitor survey administered during the peak visitation at Brooks Camp from July 22 to August 2, 2025. The survey evaluated perceptions of crowding, preferences for different management options, willingness to pay for a reservation system, and demographic data. The research team collected 854 completed surveys. This paper reveals significant findings regarding visitor preferences for congestion, as respondents demonstrated strong support for alternative management strategies. For instance, respondents identified crowding as an issue, with 70% of respondents stating that they would support policies which limit visitation.

The study documents broad support for implementing a reservation system, with most respondents indicating willingness to pay for this system. We estimate the value of a reservation system using parametric and nonparametric estimation methods, finding a range of $180-$388.

These results provide important evidence for park managers developing strategies to balance resource protection and visitor experience. The documented willingness to pay for a reservation system offers valuable insights that can inform management strategies at Brooks Camp and assist similar studies at other national parks with increasing visitation.

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CHAPTER 1: INTRODUCTION

Visitation is an important aspect of the mission of the National Park Service (NPS). The agency preserves natural and cultural resources for the "enjoyment, education, and inspiration of this and future generations" (National Park Service, 2025a). However, visitors can impact the NPS's ability to protect wildlife, cultural sites, park infrastructure, and visitor safety. Additionally, crowding and congestion, conflicting uses, and resource degradation can all impede the visitor experience (Manning, 2007). With growing visitation rates, the NPS must employ visitor management strategies to balance recreational use with environmental and resource protection.

For this study, we analyze visitation at a popular recreation site within Katmai National Park, called Brooks Camp. Home to more than 2,000 brown bears, Katmai National Park and Preserve offers one of the world's most unique wildlife-viewing opportunities. The park is located nearly 300 miles southwest of Anchorage on the Alaska Peninsula and is accessible only by float plane or boat. Brooks Camp is distinguished for its viewing platforms and on-site lodging. Being one of the only locations within the park with infrastructure to house and feed visitors, Brooks Camp is the most well-known and accessible site within Katmai. When the salmon run is at its peak each summer, 400 to 600 visitors might arrive for the day.

In 2012, webcams were installed to livestream bear activity in Brooks Camp to millions of viewers annually. These webcams have attracted attention and visitors to the site. In fact, Brooks Camp experienced a 139% increase in visitation from 2012 to 2024 (Figure 1), substantially outpacing the average 33% increase in visitation across all national parks in the United States (Lewis et al., 2025; National Park Service, n.d.).

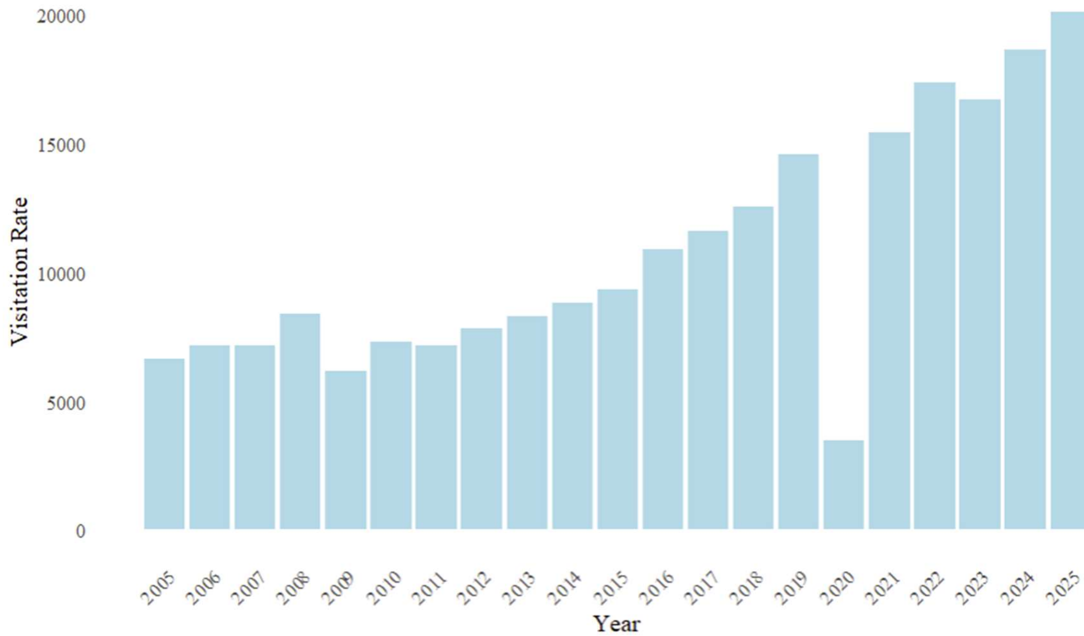

Figure 1: Approximated Visitation Rate at Brooks Camp, 2005-2025. The National Park Service requires visitors to attend a "Bear Safety Orientation" upon their arrival to Brooks Camp. The number of visitors attending this orientation is used as a proxy for daily visitation rates.

Brooks Camp has limited infrastructure and faces strict spatial constraints. As a result, visitation can place stress on NPS staff as they manage human-wildlife interactions and ensure visitor safety. To address increased visitation, popular destinations, such as Rocky Mountain National Park, are employing timed-entry reservation systems. These systems can help spread visitors throughout each day and season, reducing overall crowding (U.S. Department of the Interior, 2022). Park managers often make such management decisions with limited data regarding visitors' perceptions of crowding and preferences for management options.

To understand these perspectives, we implemented a pilot study of willingness to pay for a reservation system which would reduce congestion at Brooks Camp. Using a park visitor survey, the following research questions are addressed: What are visitors' perceptions of crowding and visitor management in Brooks Camp? What is the value associated with congestion reduction? Using parametric and nonparametric approaches, we estimate visitor willingness to pay for reduced congestion. These results provide guidance to the National Park Service and contribute to the broader literature on visitor management of public lands.

CHAPTER 2: LITERATURE REVIEW

Walls (2022) reviewed the literature regarding the economics of national parks, showing that crowding is common in most popular parks, deteriorating visitor experiences and park resources. Recently, there have been studies on the impact of social media exposure on in-person visitation in national parks, with Wichman (2024) showing that media exposure increases in-person visitation rates.

Congestion has long been a relevant topic in outdoor recreation literature with studies examining how crowding shapes the value of recreational experiences. Anderson and Bonsor (1974) were the first to show that multiple users of a recreation site impose congestion costs that affect resource valuation. Since then, revealed preference studies have demonstrated the importance of accounting for congestion in visitor welfare measures. Timmins and Murdock (2007) show that ignoring congestion at nearby recreation sites, which would increase if the main study site were closed, understates the total site value by more than 50% due to the endogeneity between site quality and crowding. The authors recognize that stated preference methods avoid the endogeneity problem between site quality and crowding because hypothetical scenarios can vary congestion levels while holding constant the unobservable attributes that motivate sorting behavior. Recreationists may choose among viewing locations based on expected crowding, which is shaped by the decision of other visitors.

Stated preference methods have also been used to show the impacts of congestion at recreation sites and opinions towards public lands management. The two main approaches are discrete choice experiments and contingent valuation methods (CVM), where respondents express their willingness to pay (WTP) for a change in a public good (Johnston et al., 2017;

Hanley & Czajkowski, 2019; Haab et al., 2020). Cicchetti and Smith (1973) estimate recreators' WTP to avoid encounters with other people during a trip, being the first empirical study of the effect of congestion on WTP. This finding highlights that visitors value solitude in wilderness areas despite offering limited insights into specific management options. McConnell (1977) uses a stated preference approach to estimate the effects of congestion on beaches, providing relevant findings for recreation sites with frequent returning visitors. These papers mark the beginning of work using stated preference methods to measure values associated with congestion on public lands.

Stated preference methods can also highlight the heterogeneity of congestion perceptions through visitor segmentation. For instance, Kang et al. (2021) use visitor satisfaction survey data to understand visitor preferences for various recreational attributes. The authors find that congestion reduces visitor satisfaction, however there are different degrees of preference between local and non-local tourists. León et al. (2015) use a discrete choice experiment to explore tourist preferences for congestion by evaluating WTP for policies that reduce crowding, restore ecosystem services, and improve resident welfare in a national park in Colombia. The authors identify three segments of visitors with varying preferences for congestion policies, suggesting optimal management can be achieved by designing visitor experiences to target each segment.

Beyond stated preference approaches, several studies incorporate other data sources, such as daily visitation, into their analyses of crowding and visitor experience. Guo et al. (2019) capture visitor preferences to estimate a visitor-acceptable standard and visitor-preferred standard for crowding at a UNESCO World Heritage Site. The authors rely on camera-captured data and entrance counts to understand visitor flows and crowding. Carr and Newbold (2025) use visitation records to develop an optimal congestion pricing framework for Yellowstone National Park, demonstrating how entrance fees can reduce crowding while maintaining social welfare and increasing park revenue. Lastly, utilizing cellphone data as a method to estimate visitation and crowding in recreation areas is becoming increasingly popular (Lawson, 2021). These papers highlight the relevance of congestion in national parks, yet they rely on external counts of crowding rather than direct measure of visitor preferences for crowding.

Shelby (1980) finds that the number of visitor interactions is not consistently determined by visitor density at a recreation site. Moreover, density and interactions do not determine a visitor's perception of crowding. Following this, Jakus and Shaw (1997) evaluate data on perceptions, mitigating behavior, and management preferences related to congestion. Both studies emphasize that the congestion perceived by the visitor may not equate to density of people within a recreation site. Therefore, we add to a gap in the literature examining important aspects of the visitor experience that cameras, entrance counts, and phone data cannot capture, such as experienced wait times, perceptions of crowding, and welfare changes associated with crowding reduction.

We make several contributions to existing literature. First, we provide the first direct valuation of a reservation system in a national park, which moves beyond congestion cost estimates and provides relevant policy guidance. Second, we capture multiple aspects of congestion, including wait times, platform crowding, and visual obstructions, which all affect visitor welfare. Finally, the wildlife viewing context and bear safety considerations introduce unique tradeoffs between crowding reduction and other visitor priorities that are absent from many recreation studies.

CHAPTER 3: THEORETICAL FRAMEWORK

Rising visitation at national parks makes visitor management a relevant policy issue. Park managers must balance growing demand with visitor satisfaction and resource protection, often with limited information about visitor perceptions. This study develops a utility framework to understand how congestion affects visitor welfare and to estimate the value of congestion reduction.

Visitors derive utility from recreating as a function of trip characteristics, congestion levels, management policies, and individual attributes. Following Jakus and Shaw (1997), congestion (c) occurs when the presence or actions of one or more visitors decreases another visitor's utility (U). Each visitor maximizes their utility subject to their income (y). The indirect utility that visitor n obtains under management scenario k is:

$$U_n = V_n(c_k, y_n - A_{k,j}, z_n) + \varepsilon_n$$

where $V(\cdot)$ is indirect utility, c_k is the level of perceived congestion which varies under policy k (k=0 is the status quo, k=1 is a reservation system). Further, y_n is income and A_k is the cost of accessing the site under policy k (equal to \$0 under status quo and a specified increase in trip costs when k=1), where the trip cost increase varies across offered bid amounts, j. In dichotomous choice contingent valuation (CV) scenarios, n respondents are each offered one of j bid amounts to evaluate WTP across varying costs. z_n is a vector of observable visitor and trip characteristics, for instance how many bears an individual sees. Lastly, ε_n is an independently and identically distributed error term with a mean of zero.

Crowding imposes costs in multiple ways. Higher levels of congestion reduce aesthetic enjoyment of wilderness, increase wait times, limit visibility of scenery, and may increase human-wildlife interactions. While these dimensions of congestion are distinct, they all increase with total daily visitation. Therefore, congestion is modeled as a single index that declines under the reservation system ($c_1 < c_0$). Though visitor tolerance for crowding varies, congestion is assumed to have a net-negative effect on utility ($\partial V / \partial c < 0$).

Expectations play a role in perceptions and tolerance of congestion. Visitors whose expectations are shaped by viral webcam content may experience greater disappointment when faced with crowds, while guided tour clients warned of long waits may exhibit higher tolerances. This heterogeneity in expectations and preferences motivates the individual-level stated preference approach employed in this study. Preferences are captured by the visitor characteristics term z_n since the survey collects data on demographics, trip characteristics, and individual attitudes towards crowding and safety.

A contingent valuation (CV) approach elicits compensating variation, the maximum amount a visitor would pay for reduced congestion while maintaining the same utility level. A reservation system increases utility by reducing congestion but decreases utility by increasing trip costs. Following the framework proposed by Hanemann (1984), a visitor accepts the proposed increase in trip costs, $A_{1,j}$, if the utility gained from reduced congestion is greater than the income lost from paying the additional cost:

$$V_n(c_1, y_n - A_{1,j}, z_n) + \varepsilon_1 > V_n(c_0, y_n, z_n) + \varepsilon_0$$

The CV scenario presents visitors with a randomly assigned bid amount, asking whether they would support the reservation system at a specific additional cost. Using a dichotomous choice question response format provides the most straightforward approach to confirm incentive compatibility for public goods, especially when surveys use a single-choice question (Johnston et al., 2017). Issues present in open-ended or iterative-bidding questions are addressed by the dichotomous choice format. Moreover, this question format even resembles the nature of many marketplace purchases (Peterson, 2003). In this scenario, a yes-response indicates that the respondent's WTP is greater than the offered bid amount, while a no-response indicates that their WTP is less than the offered bid amount. To find the probability that the individual answers "Yes" to the proposed bid amount, let $\varepsilon = \varepsilon_1 - \varepsilon_0$ and $\Delta V = V(c_1, y - A_{k,j}, z) - V(c_0, y, z)$. This allows the probability of a yes-response to be modeled as:

$$Pr(yes) = F_{\varepsilon}(\Delta V) = (1 - G(\cdot))$$

where $F(\cdot)$ is the cumulative distribution function of the random variable ε, and $G(\cdot)$ is the cumulative distribution function of WTP (Hanemann, 1984). The probability of a yes-response varies as a function of observable characteristics and unobserved preferences. This paper examines how these trip characteristics and individual preferences predict WTP, identifying which factors are strong influences on the value of congestion reduction.

CHAPTER 4: PILOT STUDY SITE

There are limited economic studies on Katmai National Park. Lewis et al. (2024a) conducted a visitor survey at Brooks Camp in 2023, collecting information on perceptions of crowding and the influence of explore.org webcams on visitor experience. Fitz et al. (2021) and Richardson and Lewis (2022) conducted two online surveys of viewers of these webcams to better understand viewer preferences and estimate the value placed on the preservation of individual bears in Katmai. Richardson et al. (2017) explored how applying travel cost demand models can be difficult for remote destinations such as Katmai National Park. Our study contributes to the literature by understanding preferences of Brooks Camp visitors.

According to Katmai National Park visitation data, the majority of visitors arrive in July and August (National Park Service, 2021). Peak visitation coincides with the height of the sockeye salmon run, which brings both fish and bears to the Brooks River. There is currently no capacity limit on daily visitation. Visitors typically travel to Brooks Camp on a floatplane or water taxi. Commercial operators of air and water taxis must have a valid Commercial Use Authorization (CUA) and operators are limited to bringing a maximum of 90 clients to Brooks Camp daily (National Park Service, 2025d). There are approximately 48 CUA holders and concessioners in Katmai National Park (National Park Service, 2026).

Brooks Camp closes its facilities from September 17 to June 1, causing visitation to be concentrated to just three and a half months in the year. Even when Brooks Camp facilities are open, on-site lodging is limited, with capacity for 64 visitors in cabins and 60 visitors in the campground. In 2025, the cabins cost $1,260 per person per night and are allocated by lottery, while the campground must be reserved and costs $18 per person per night (Bristol Adventures, n.d.; National Park Service, 2025c). Therefore, most visitors come for a one-day trip, called a "day trip" hereafter (Lewis et al., 2025).

Visitors arrive either on Naknek Lake or Lake Brooks, attend a required NPS orientation to learn about bear safety, and then typically head to the Falls platform by walking along the trails (Figure 2). It is common for visitors to encounter bears and get caught in "bear jams" on the trails. In these instances, visitors are instructed to step off the trail and wait for bears to pass through the area, often causing many people to get stuck in an area at once. NPS staff are sometimes present to manage visitor behavior and, if needed, to haze the bears away from humans. These situations can become tense for staff and visitors, particularly if ranger guidance or bear safety protocol is ignored.

Figure 2: Map of Brooks Camp. From *Brooks Camp – Katmai National Park & Preserve,* by National Park Service (2024), U.S. Department of the Interior, Public domain.

While there are several designated bear-viewing platforms in Brooks Camp, the Falls platform is the most popular because visitors can watch bears fish over a waterfall (Figure 3).

This platform has capacity for 40 people at one time. When more than 40 people try to access the platform, NPS rangers manage a waitlist, allowing each person 30 minutes on the platform at a time. The waitlist is first-come, first-served, and wait times can extend over two hours during the busiest times of the season. When the Falls platform is at capacity, there are obstructed views of the waterfall and photographers have difficulty taking pictures because people are standing elbow-to-elbow.

Figure 3: Falls Platform. From *Brooks Falls Platform– Katmai National Park & Preserve*, by National Park Service (2025b), U.S. Department of the Interior, Public domain.

These viewing platforms have webcams attached to them that livestream bear activity from late June through October. The webcams receive millions of views annually. Each year, over 100 bears typically return to the Brooks River (Fitz, 2021). These bears are identified by numbers and sometimes nicknames. At the end of the salmon run, explore.org hosts Fat Bear Week, an annual online competition which celebrates bears as they prepare for hibernation. The contest is covered by major media outlets including *The New York Times*, *Forbes*, and national television networks. In 2025, Fat Bear Week received 1.6 million votes from viewers, the most in competition history (Kircher, 2025). This event draws attention to the park, inspiring new visitors to travel to Brooks Camp. This trend is consistent with findings that social media exposure impacts recreation demand within parks (Wichman, 2024).

Using the attendance of the mandatory orientation required for all visitors as a proxy for site visitation, an estimated 20,068 people visited Brooks Camp in 2025 (Lewis et al., 2025). The orientation count underestimates daily visitation, as some registered guides are authorized to give their clients a bear safety briefing instead of sending them to the NPS orientation, so these groups are not included in the daily count. While Brooks Camp has low visitation relative to most popular national parks in the U.S., this site is particularly relevant for a congestion study due to its strict spatial constraints, short peak visitation season, and iconic wildlife viewing opportunities. With limited protected viewing platforms and a high concentration of both bears and people, Brooks Camp faces unique management challenges that differ from typical high-traffic recreation areas.

Specific site characteristics impact the nature of visitation to Katmai National Park. Importantly, adverse weather disrupts concessioners' ability to fly and land on the lakes surrounding Brooks Camp. In these instances, pilots must wait for the weather to pass before flying visitors in. This condenses all arrivals to just a few hours of the day and limits options for reservation system design. For instance, a timed-entry system is infeasible for Brooks Camp.

CHAPTER 5: SURVEY

Survey Design

The survey was designed in early 2025 by Lynne Lewis, Leslie Richardson, Laura Taylor, and Mike Fitz. Questions were developed based on previous survey efforts, including an on-site visitor survey administered at Brooks Camp in 2023 and two online surveys of webcam viewers in 2019 and 2020 (Lewis et al., 2024a; Fitz et al., 2021). New questions were added and existing questions were altered to address current issues relevant to park managers, such as wait times and visitor safety. Two focus groups were conducted, with participants recruited through the Bears of Brooks Falls Facebook page which resulted in eleven pretest participants and nine focus group participants.

The survey included questions on trip characteristics, visitor experience, perceptions of crowding and safety, wait times, management preferences, knowledge of bears and webcams, and demographics. A contingent valuation question was included to estimate visitor willingness to pay for reduced crowding via a reservation system. Since the reservation system is hypothetical, a stated preference approach is necessary. Revealed preference data cannot yet capture behavioral responses to such a policy, and it is not feasible to simulate real-world choices through experimental reservation systems or reduced crowds.

The contingent valuation scenario asks respondents how they value an improved visitor experience, specifically a wait time of (at most) 15 minutes and unobstructed views, by way of a reservation system. The CV question did not explicitly state that a reservation system would reduce visitors' ability to access Brooks Camp on specific dates due to a capacity quota. The scenario was presented as follows:

> *Currently, access to Brooks Camp does not require a reservation. However, a reservation system could be implemented to reduce crowding and reduce the wait time to access the Brooks Falls viewing platform. The benefit of a reservation system would be that there would be fewer people at Brooks Camp each day. Visitors could expect wait times of 15 minutes or less to get on the platform and visitors would have unobstructed views of the bears and river when on the platform.*

There is no entrance fee to visit Brooks Camp, so the payment vehicle focused on overall trip costs rather than an increase in entry fees. The CV scenario uses a single, dichotomous choice question format. The question concluded as follows:

> *Considering the benefits of less crowding, would you support such a reservation system even if it meant your personal costs for this most recent trip to Brooks Camp were $X higher than the total amount you paid for this trip?*

The *$X* was randomly filled with one of seven bid amounts: $5, $15, $35, $75, $125, $200, and $325. Focus group participants suggested removing a proposed $500 bid amount, therefore $325 was the highest bid offered.

Follow-up questions were included to evaluate the validity of responses to the question. Individuals who responded "No" were asked to identify their most relevant reason for doing so. This question allowed us to evaluate the validity of responses to the valuation scenario and give respondents the opportunity to indicate if they would pay a different amount for additional trip costs (Johnston et al., 2017).

Survey Administration

To deliver the survey, a team of two researchers intercepted visitors at Brooks Camp over a 12-day period from July 22, 2025, to August 2, 2025. This time frame allowed the research team to explore visitation patterns and visitor opinions during the most visited weeks of the summer at Brooks Camp.

Surveys were administered using electronic tablets at a variety of locations throughout Brooks Camp, including the waiting area near the Falls platform (the “Treehouse”), the Brooks Camp Visitor Center, and Brooks Lodge. The Treehouse was the most common survey location because visitors could be intercepted upon leaving the Falls platform or while on the waitlist. Any visitor over the age of 18 was eligible to participate. We intercepted nearly every visitor that we encountered, totaling more than 1,000 visitor intercepts over the sampling period. In total, 669 surveys were completed at the Treehouse, 181 at Brooks Lodge, and 4 elsewhere, for a total of 854 responses.

Using the NPS daily orientation rates, Table 1 shows an average of 338 visitors arriving to Brooks Camp each day during the survey period, with an overall high of 436 visitors on July 28 and a low of 241 visitors on July 25 (Lewis et al., 2025). These daily records do not account for visitors who are on-site for multiple days or visitors who attend orientation with a certified guide. Therefore, Table 1 underestimates the number of on-site visitors by approximately 100 people per day.

Table 1: Visitation Numbers during Survey Period.

Date	Orientation Attendance
7/22/25	405
7/23/25	388
7/24/25	411
7/25/25	241
7/26/25	381
7/27/25	325
7/28/25	436
7/29/25	310
7/30/25	293
7/31/25	332
8/1/25	275
8/2/25	254

CHAPTER 6: DATA

Demographics

As depicted in Table 2, 50.3% of respondents were female and 48.1% were male. The most common age category (25.2%) was 65 years and older. Most respondents are employed full-time (50.3%). The majority of respondents (75.5%) hold a bachelor's degree or higher, with 40% holding a graduate degree. The most common household size was 2 people (54.5%). In terms of income, 33.9% have income between $100,000 and $200,000 and 37.7% have income over $200,000 annually. Lastly, 88.2% of respondents reside in the United States.

Table 2: Respondent Demographics (854 observations)

Characteristic	Category	Percent
Gender	Female	50.3%
	Male	48.1%
	Prefer not to answer	1.6%
Age	18-24	5.9%
	25-34	17.3%
	35-44	17.6%
	45-54	15.7%
	55-64	18.3%
	65 or older	25.2%
Employment	Full-time	50.3%
	Self-employed	12.7%
	Part-time	5.8%
	Unemployed	1.4%
	Retired	27.2%
	Other	2.5%
Education	Less than high school	0.5%
	High school graduate or GED	7.3%
	2-year degree	6.1%
	Trade/technical school	2.9%
	Some college	7.7%
	4-year degree	31.3%
	Some graduate school	4.2%
	Graduate school	40.0%
Household Size	1	18.3%
	2	54.5%
	3	10.9%
	4 or more	16.3%
Income	Less than $50,000	10.5%
	$50,000-$100,000	17.8%
	$100,000-$150,000	16.6%
	$150,000-$200,000	17.3%
	More than $200,000	37.7%
Residence	United States	88.2%
	United Kingdom	1.7%
	Canada	1.2%
	Other	8.9%

Trip Characteristics

The majority of respondents (80.4%) were on their first trip to the park in the past 5 years. 75% of all visitors were on a day trip to Brooks Camp. Nearly all respondents (98.7%) reported that they plan to watch bears during their visit. Further, 88.7% of respondents were on the Falls platform at least once before taking the survey. When going to the Falls platform, only 17.7% of respondents experienced no wait time. Lastly, 72.2% of respondents knew about the explore.org webcams prior to their trip.

Congestion

The survey included questions on perceived crowding and preference for different management options. First, we asked visitors how different factors contributed to their experience at Brooks Camp. The number of visitors, the number of people on the platforms, and the wait time to get on the platform contributed more negatively to the visitor experience than other factors, such as interactions with rangers or the number of bears (Figure 4).

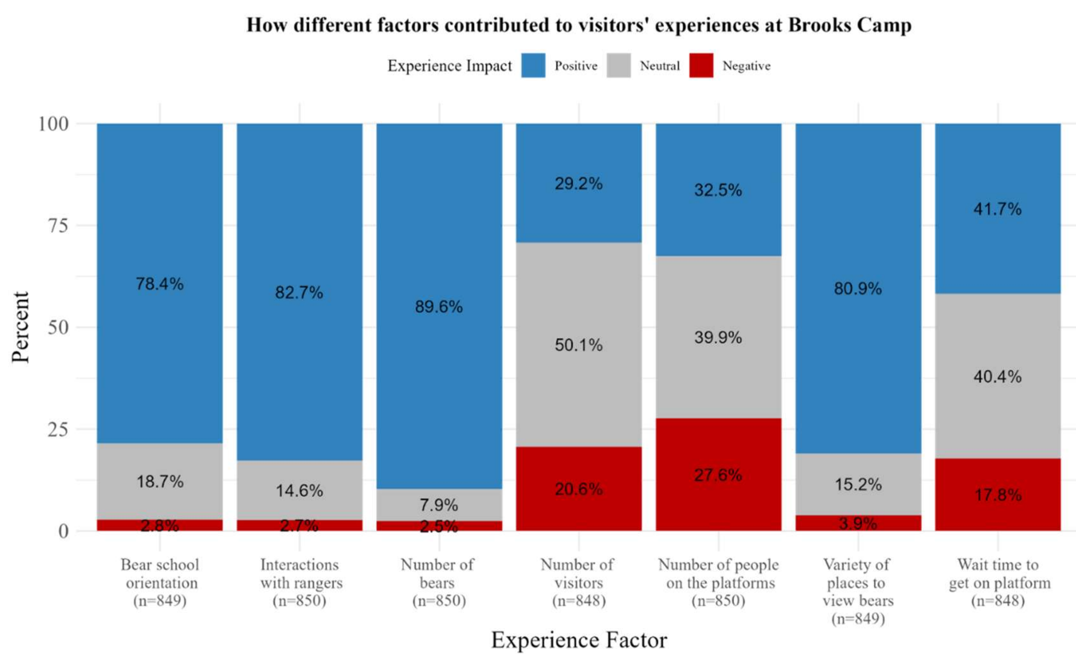

Figure 4: Visitor Experience in Brooks Camp.

Evidence suggests that respondents experienced the negative impact of crowding as most respondents (62.7%) agree that they would be less likely to visit Brooks Camp in the future if crowding continued to increase (Figure 5).

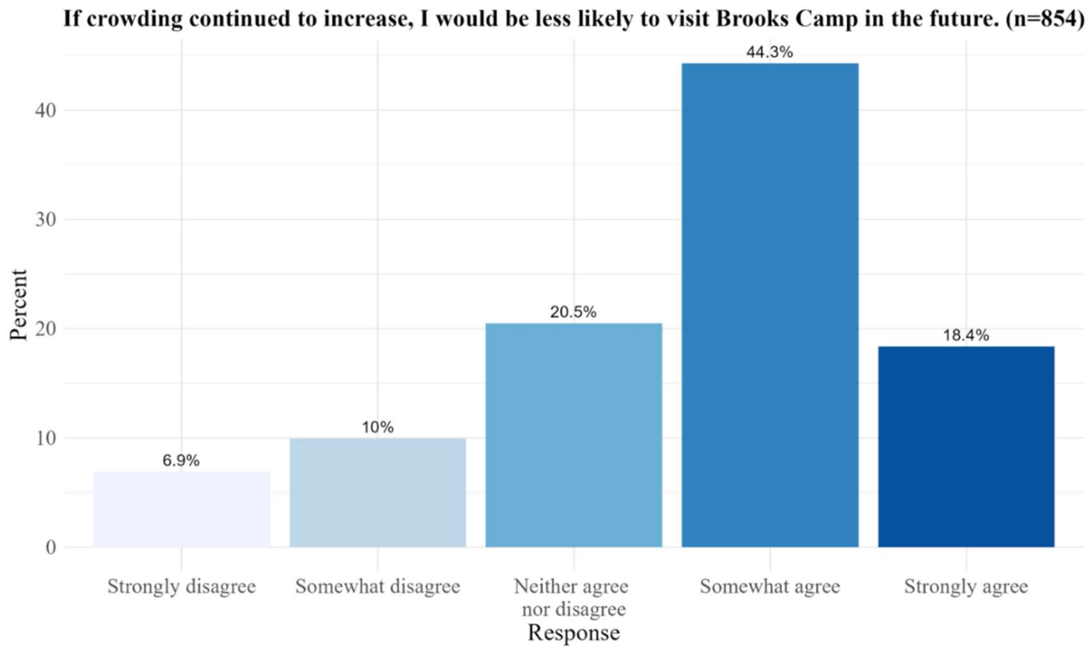

Figure 5: Crowding Impacts on Future Visitation (Among All Respondents)

We find that 83.4% of respondents who report that they were negatively impacted by the number of visitors state that they would be less likely to visit Brooks Camp in the future if crowding increased (Figure 6). Conducting a Kruskal Wallis test determines that respondents' likelihood of visiting Brooks Camp in the future varies based on their experience with crowding during their visit (see Appendix E).

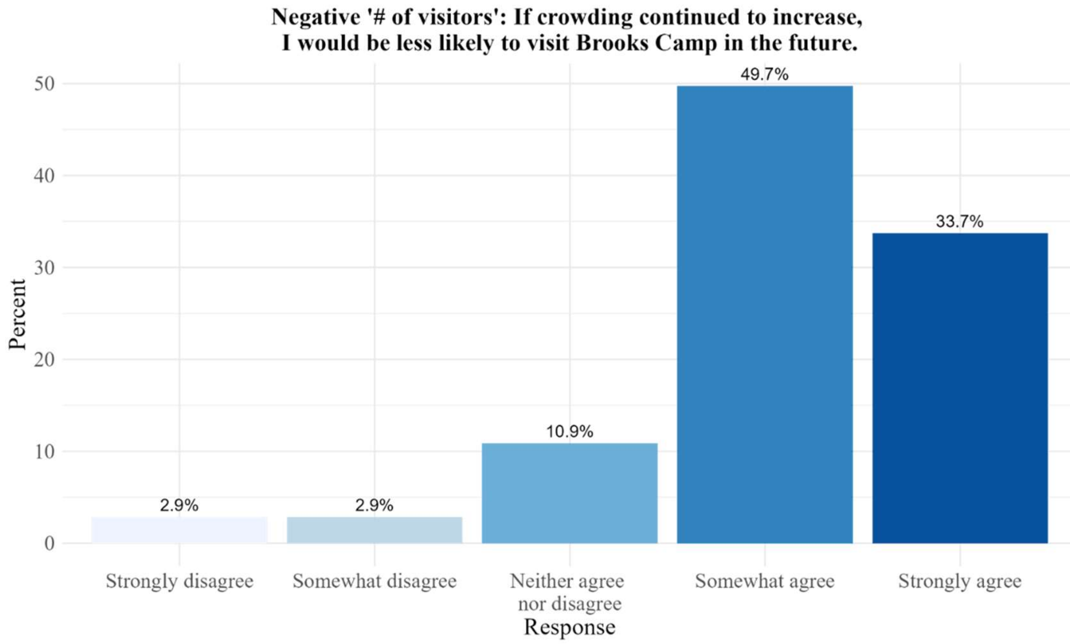

Figure 6: Impacts of Crowding on Future Visitation (Among Respondents Who Reported That Their Experience Was Negatively Impacted by the Number of People at Brooks Camp).

Moreover, there is substantial support for limiting congestion, as 70.3% of respondents stated that they would support policies aimed at reducing crowding at Brooks Camp even if it meant it would be more difficult for them to visit the park on a specific day (Figure 7).

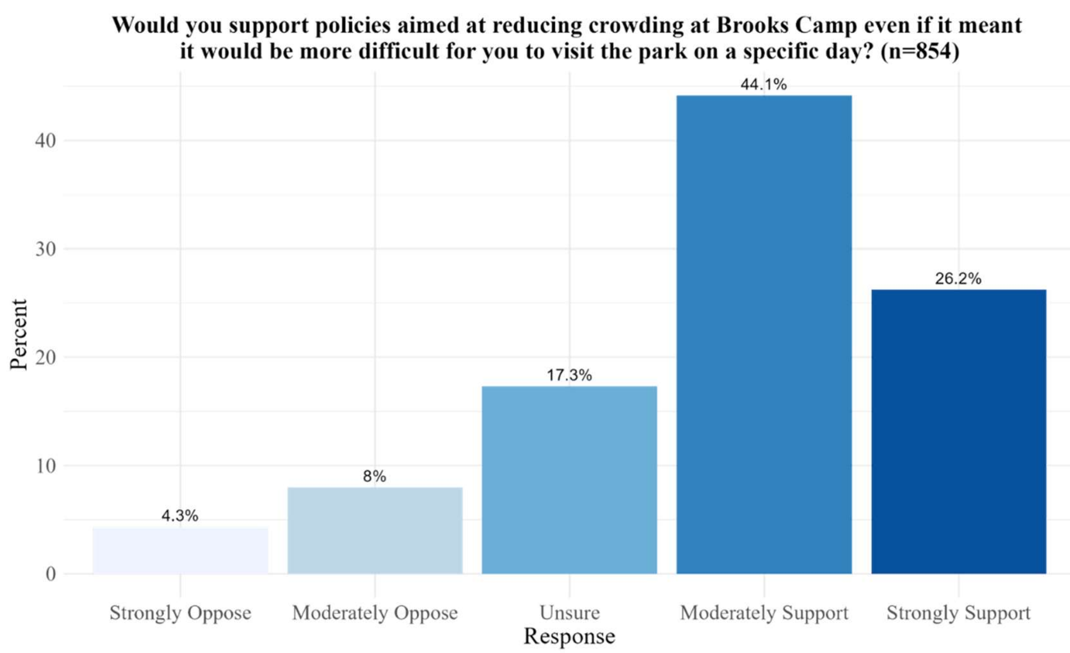

Figure 7: Support for Policies which Reduce Crowding (Among All Respondents)

Figure 8 shows that respondents who reported that they were negatively impacted by the number of visitors showed stronger support for such policies, with 78.3% of these respondents stating either somewhat or strong support. The Kruskal Wallis test indicates that respondents' support for policies varies based on whether respondents were positively or negatively impacted by the number of visitors at Brooks Camp (see Appendix E).

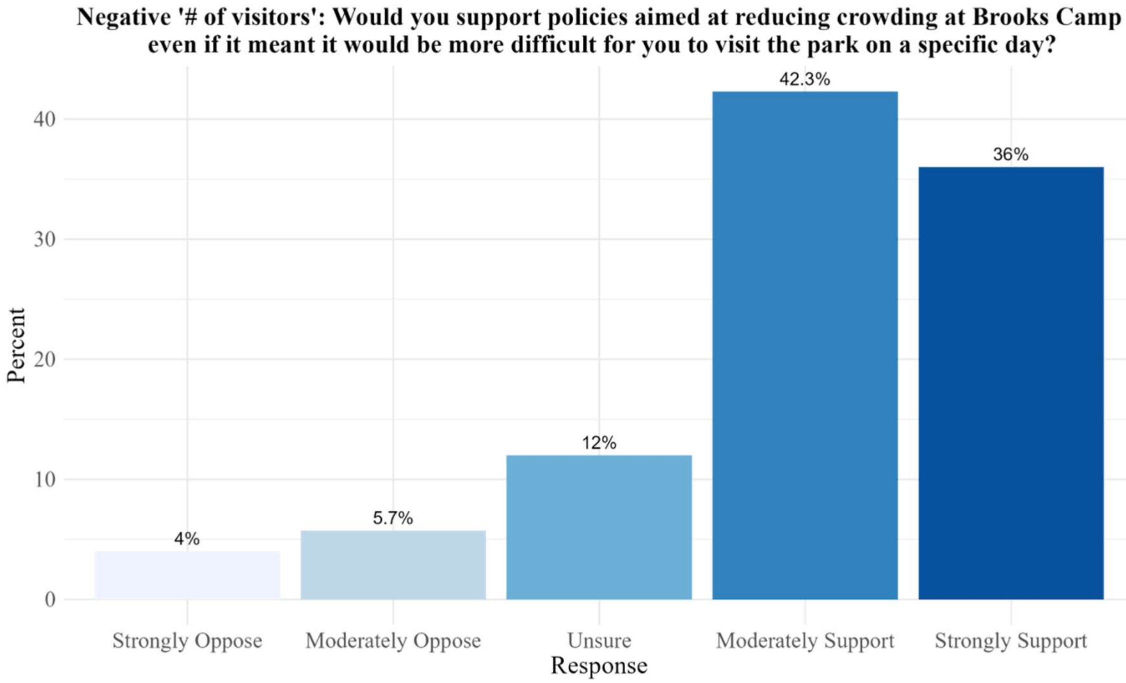

Figure 8: Support for Policies which Reduce Crowding (Among Respondents Who Reported That Their Experience Was Negatively Impacted by the Number of People at Brooks Camp).

Moreover, there is broad support for limiting visitation for the following reasons: protecting visitor experience (71.3%), protecting visitor safety (65.1%), reducing environmental impacts (75.4%), and protecting bears and wildlife (81.5%) (Figure 9). Substantially more respondents (16.4%) support limiting visitation to protect wildlife than to protect visitors' safety.

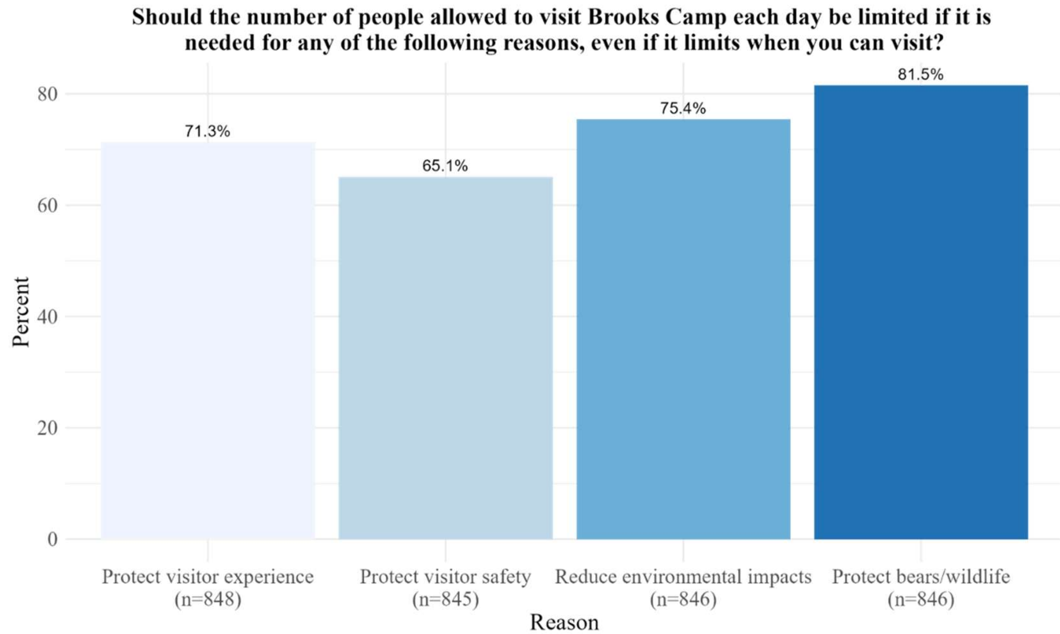

Figure 9: Support for Reasons to Limit Visitation (Among All Respondents).

Across each reason to limit visitation, Figure 10 demonstrates that there is more support from overnight visitors than day trip visitors. For instance, 75.5% of respondents on overnight trips prefer to limit visitation to protect visitor safety compared to 61.6% of respondents on day trips.

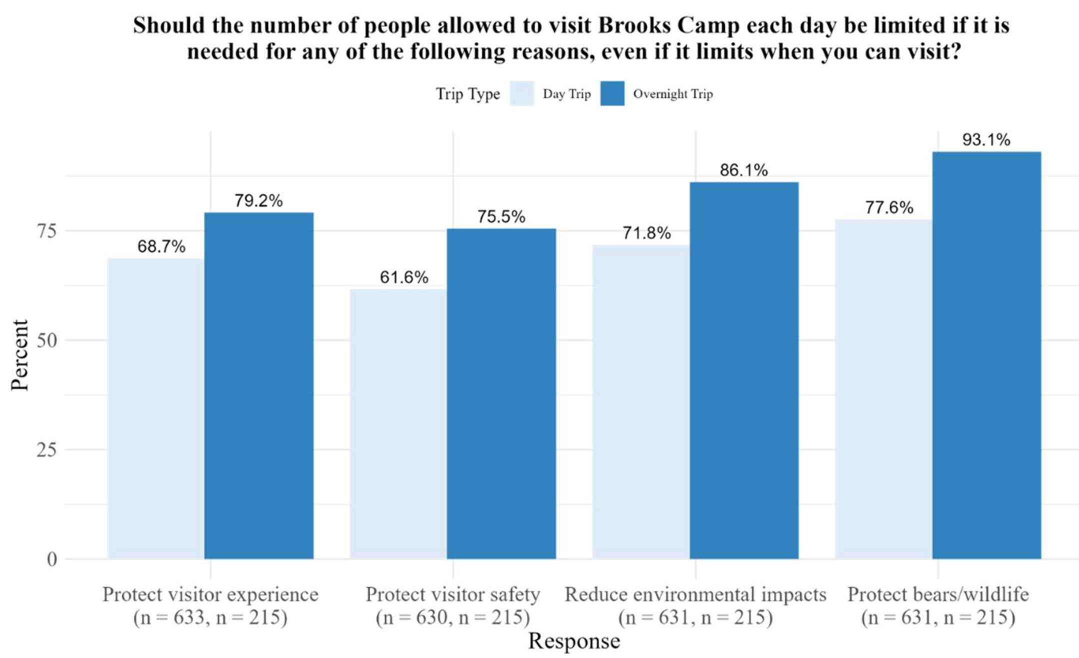

Figure 10: Support for Reasons to Limit Visitation (Comparing Day Trip Respondents and Overnight Trip Respondents).

When choosing among options to reduce congestion, 79.2% of respondents on an overnight trip would most prefer limiting people who are visiting just for the day, compared to 57.1% of respondents on a day trip (Figure 11). Additionally, 19.9% of day trip respondents stated that there is no need to reduce congestion, compared to only 8.8% of overnight trip respondents. Therefore, there are notable differences in opinions between visitor segments.

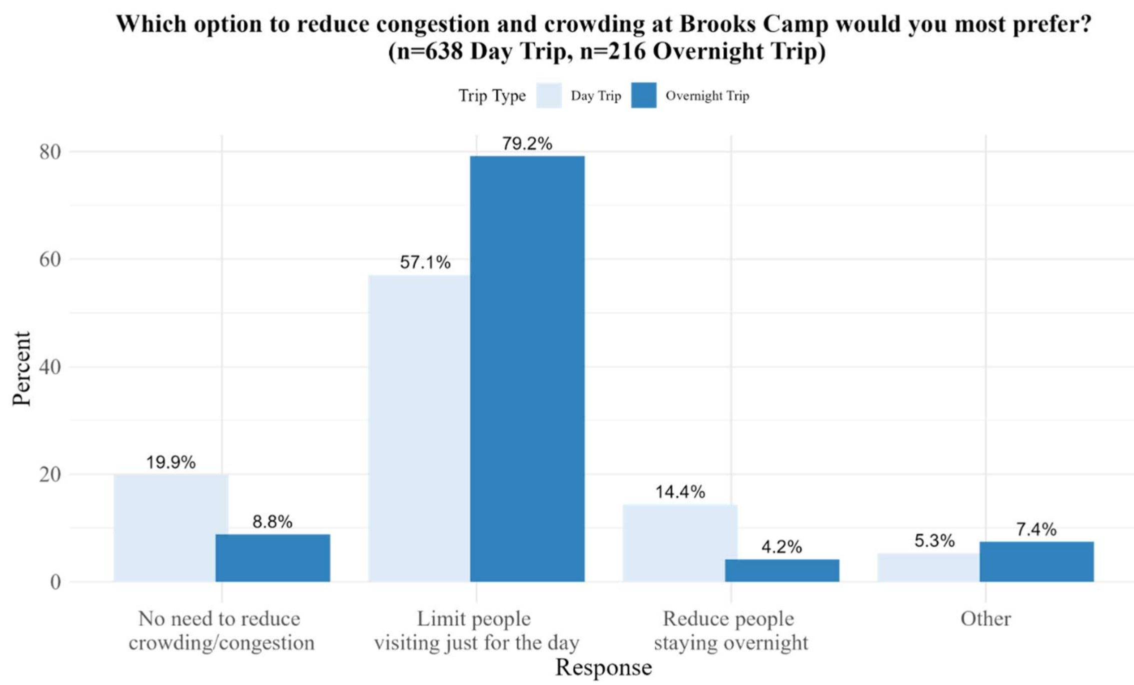

Figure 11: Preferred Option to Reduce Crowding (Comparing Day Trip Respondents and Overnight Trip Respondents).

Analyzing responses to congestion questions reveals that overnight visitors more strongly favor limits on visitation. Moreover, there are important differences between visitors who report experiencing the negative impacts of crowding. These insights are notable as we evaluate heterogeneity in visitors' willingness to pay.

Willingness to Pay

In total, 841 survey respondents (98.5% of all respondents) answered the contingent valuation question. Figure 12 shows the percentage of yes-responses to each of the seven bid amounts. The demand curve is downward sloping, with acceptance rates declining from 75.8% at the lowest bid of $5 to 47.9% at the highest bid of $325.

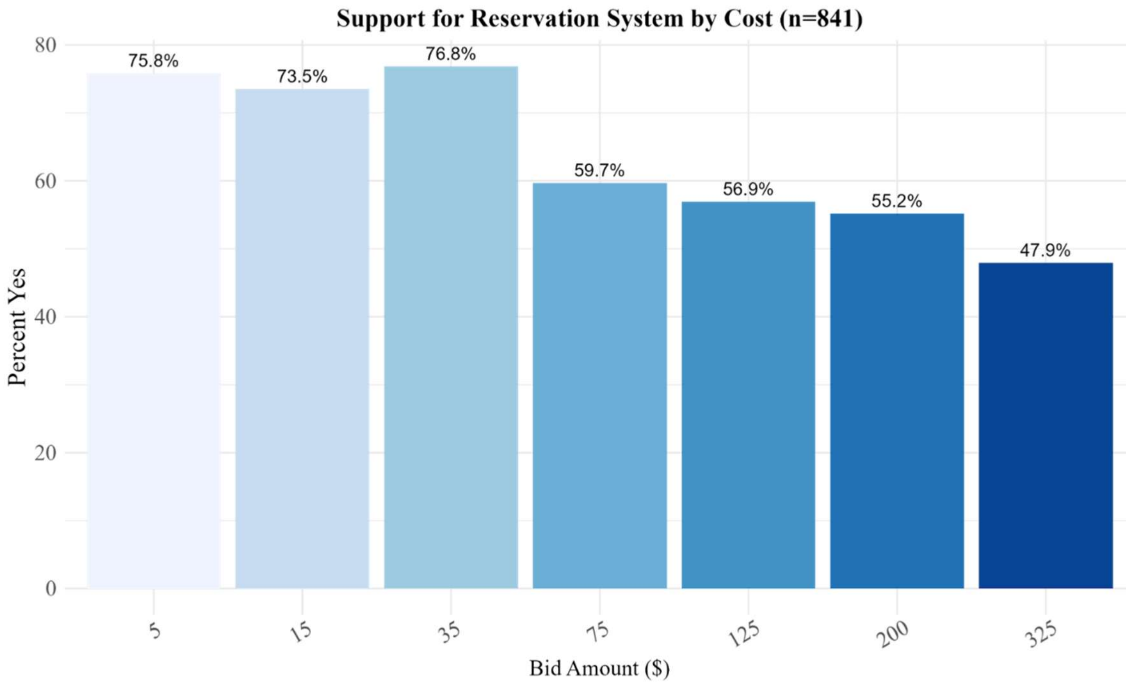

Figure 12: Percent of Yes-Responses to Contingent Valuation Question.

The data contain several features that complicate traditional estimation of willingness to pay. First, there is non-monotonicity, with the percentage of yes-responses being 73.5% at $15, increasing to 76.8% at $35, then decreasing to 59.7% at $75. Therefore, the acceptance rate does not decline smoothly as the bid amounts increase. Further, there is both a fat tail and a flat tail (Lewis, et al., 2024b). The yes-response rate declines slowly at the highest bid amounts, decreasing from 59.7% at $75 to 47.9% at $325 (flat tail). Additionally, the right tail of the yes-response function shows that acceptance rates are high even at the highest bid amounts, as nearly half of respondents (47.9%) accepted the $325 bid (fat tail). The absence of a bid amount where acceptance is zero, known as a choke price, suggests the true WTP distribution extends beyond $325. The lack of a choke price introduces uncertainty about the upper tail of the distribution.

Table 3 shows the total number of respondents offered each bid amount, confirming that each bid amount was presented to a sufficient number of respondents for statistical analysis.

Table 3: Frequency of Bid Amounts Offered in the Contingent Valuation Question.

Bid	Percent Yes-Responses	N
$5	75.8%	122
$15	73.5%	120
$35	76.8%	96
$75	59.7%	126
$125	56.9%	124
$200	55.2%	118
$325	47.9%	148

Respondents who answered “No” to the contingent valuation question were asked to state the reason they are not willing to pay, which allows us to identify protest responses (Table 4). A protest response is when the respondent has answered “No” to the CV question but then indicates that their value of the good is not truly zero (Carson and Hanemann, 2005). In our case, a respondent protests when they answer “There should be a reservation system, but it should be free” because they value congestion reduction, however they do not want to pay for it. Overall, 36% of the “No” responses (133 individuals) were protests.

Table 4: Reason for a "No" Response to the Contingent Valuation Question.

Reason	Percent Responding	N
Brooks Camp is not too crowded	17%	52
There should not be a reservation system	25%	78
There should be a reservation system, but it should be free	36%	113
I cannot pay that amount, but I would pay different amount	3%	9
I cannot afford it	12%	36
Other	8%	24

Protests can be dropped from the analysis if the researchers consider them to be invalid responses (Carson and Hanemann, 2005). Including protests means that WTP estimates are conservative. An analysis of WTP estimates which exclude protest responses is displayed in Appendix D.

CHAPTER 7: EMPIRICAL METHODS

Willingness to pay estimates can be sensitive to the empirical model used (Bengochea-Morancho et al., 2005; Hanemann and Kanninen, 1999; Kriström, 1990; Lewis et al., 2024), therefore it is important to evaluate multiple potential methods given the functional form of the data. To estimate WTP for reduced crowding at Brooks Camp, both parametric and nonparametric estimators are employed. If the parametric and nonparametric results converge, there is confidence that results are not driven by the functional form assumptions. However, nonparametric approaches may be more appropriate if parametric models impose incorrect assumptions on the data.

Parametric Approach

Parametric approaches are common in willingness to pay estimation because these models allow incorporation of covariates into willingness to pay functions which can be useful for policy purposes (Carson & Hanemann, 2005). This paper looks specifically at the probit model. The probit estimates the probability that a respondent's willingness to pay exceeds the randomly assigned bid amount. If the respondent answered "Yes" to the CV question, then their WTP is greater than or equal to the bid amount. If they answer "No", then their WTP is less than the bid amount.

Estimating willingness to pay via a probit model requires the researcher to regress CV responses on the bid amounts and covariates, and then to calculate WTP given these estimated parameters. Following Haab and McConnell (2002, p. 52), willingness to pay can be modeled as a linear function of observable visitor characteristics:

$$WTP(z_n, \eta_n) = \gamma z_n + \eta_n$$

where γ is a matrix of parameters, z_n is a matrix of observable characteristics associated with respondent n, and η_n is a random error term with mean zero that captures unobservable factors affecting WTP. A respondent answers "Yes" to the offered bid amount, A, if their willingness to pay (WTP) exceeds A. Assuming the error term is normally distributed, this becomes a standard probit model, where the probability of a yes-response is:

$$r(yes|z_n, A_J) = Pr(WTP_n > A_J) = Pr((\gamma z_n - A_J) > \eta_n = Pr((\gamma z_n - A_J)/\sigma > \theta_n)$$

where *z* and *A* are covariates with coefficients γ/σ and *-1/σ*. θ_n is normally distributed with a mean zero. This specification allows the bid amount and visitor characteristics to determine the probability of a yes-response.

A key advantage of the probit model is its ability to measure how observable characteristics influence willingness to pay. This makes it possible to test whether certain visitor segments have systematically higher WTP. Additionally, it provides an efficient point estimate of mean WTP under the assumption that the error term is normally distributed. Haab and McConnell (2002) state that the WTP estimates will not be particularly sensitive to the selected distribution of the error term or the functional form of the preference function when the pattern of responses is well behaved. However, if the error term is not normally distributed or the data are not well behaved (e.g. acceptance rates are non-monotonic or the right tail is poorly defined), WTP estimates can become sensitive to these modeling assumptions, raising concern about estimates of mean WTP and parameters on the covariates.

The Bayesian probit model offers another approach for estimating WTP. Rather than using maximum likelihood to estimate parameters, the Bayesian probit computes the posterior distribution of parameters by combining prior distribution with the likelihood of observed data (Albert & Chib, 1993). This model is useful for small sample sizes and quantifying uncertainty through credible intervals. While offering advantages over the standard probit, the Bayesian probit still imposes parametric assumptions on the data.

Nonparametric Approaches

Nonparametric methods are appealing since they do not impose assumptions on the functional form of the data, offering a less restrictive approach to estimating willingness to pay. The Turnbull (1976) model provides a lower bound estimate of WTP. Similar to the probit model, the Turnbull assumes a yes-response indicates a WTP at least as high as the offered bid amount and a no-response indicates a WTP lower than the offered bid amount. However, since the Turnbull does not assume a specific functional form, it provides a flexible alternative to parametric models when the data is not well behaved (Richardson & Lewis, 2022). Following Haab and McConnell (2002, p. 73), the Turnbull estimator calculates:

$$E_{LB}(WTP) = \sum_{j=0}^{J} A_j(F_{j+1} - F_j) = \sum_{j=0}^{J} A_j f_{j+1}$$

where each respondent is offered one of J bid amounts, indexed by j. F_j is the proportion of no-responses to bid A_j. The term $(F_{j+1} - F_j)$ represents the fraction of the population whose WTP falls between consecutive bid amounts. By weighing each bid by this fraction and summing across all bids, a lower bound average willingness to pay is obtained.

This method requires two assumptions. First, higher bids produce lower acceptance rates. Non-monotonicities in the WTP data must be pooled back to enforce this assumption. Second, WTP is bounded, so there exists some maximum amount beyond which no one would pay. This model treats the upper bound as the highest offered bid, truncating WTP at this amount.

The Turnbull estimator’s main advantage is robustness. It does not assume any particular error distributions and provides conservative estimates. However, it cannot incorporate covariates to explain respondent heterogeneity. Additionally, truncating at the highest bid can be problematic if there is a high yes-response rate at the highest bid, as this indicates that true WTP for many respondents extends beyond the highest offered bid.

An alternative to the Turnbull model, Kriström (1990) estimates WTP by utilizing linear interpolation between bid amounts and to represent the bid distribution beyond the specified bid range. This method assumes that the distribution is piece-wise linear between each bid amount (Haab and McConnell, 2002, p. 78). Mean WTP is determined by integrating under the piece-wise linear curve. WTP can be calculated using the Spearman-Karber estimator of the mean (Boman et al., 1999; Church and Cobb, 1973; Richardson and Lewis, 2022):

$$E(WTP) = \sum_{j=0}^{J} \frac{1}{2}(A_j + A_{j+1})(P_j - P_{j+1})$$

where P_j is the proportion of yes-responses to bid amount A_j.

The Kriström model also requires the researcher to enforce monotonicity across the bid range, pooling back any non-monotonic features. Also, this model uses linear interpolation based on responses to the highest two bid amounts to extrapolate a price where the probability of a yes-response is zero. While this allows estimation beyond the observed bid range, the estimates are sensitive to this choke price, which is based on just two data points. For this reason, when the data contains fat tails or flat tails, this estimator typically provides upper bound estimates.

To overcome this limitation, Lewis et al. (2024b) and Richardson and Lewis (2022) developed the Kriström adjustment, which replicates Kriström (1990) but estimates a choke price by interpolating across the entire bid range. This often allows for a more reasonable upper bound estimate of WTP, particularly when yes-responses to the highest bid amounts are similar which results in a flat slope at the right-tail of the bid distribution. Since estimates are sensitive to choke price, Lewis et al. (2024b) and Richardson and Lewis (2022) find that their Kriström adjustment tends to produce more reliable estimates of central tendency for WTP, particularly when fat and flat tails are present.

The last nonparametric approach employed in this study is the Bayesian Additive Regression Trees (BART) model, a nonparametric, machine learning approach. Following Chipman et al. (2010), BART approximates the function for bid acceptance as a sum of m regression trees:

$$Y = \sum_{j=1}^{m} g(x; T_j, M_j) + \varepsilon, \qquad \varepsilon \sim N(0, \sigma^2)$$

where each $g(x; T_j, M_j)$ is a regression tree defined by a binary tree structure T_j and a set of terminal node parameters M_j, and x is a vector of covariates including the bid amount and visitor characteristics. For a model where Y is binary, Chipman et al. (2010) extends BART to a probit model:

$$p(x) \equiv P[Y = 1|x] \ = \phi[G(x)], \qquad \text{where } G(x) \equiv \textstyle\sum_{j=1}^{m} g(x; T_j, M_j)$$

To estimate willingness to pay, BART first builds many classification trees which create binary splits in the covariate and bid data, creating subsamples that are homogenous in their survey responses. Each tree in the sum is constrained by a regularization prior, so each tree explains a small portion of the overall fit which prevents overfitting (Chipman et al., 2010). The structure of classification trees, displayed in Figure 13, allows the model to identify interactions and nonlinearities in the data. Using these trees, the model predicts whether each subsample will accept each of the offered bid amounts. BART produces Markov Chain Monte Carlo (MCMC) samples of the posterior WTP distribution. Second, the model integrates under the probability curve for each MCMC sample, which yields credible intervals and posterior distributions (Follett et al., 2026; Tan and Roy, 2019). Follett et al. (2026) are the first to apply the BART model to CV data.

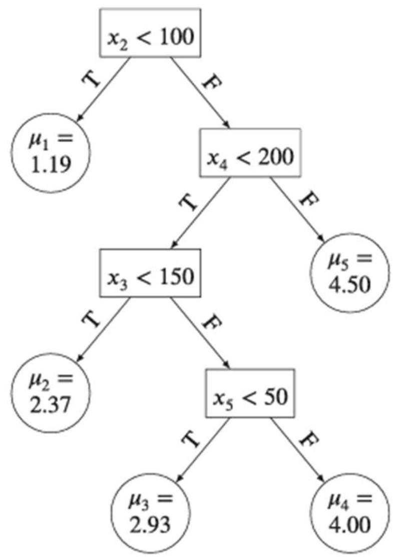

Figure 13: Example of a Regression Tree, where μ_i is the mean parameter of the i^{th} node for the regression tree. Reprinted from "Bayesian Additive Regression Trees and the General BART model," by Tan, Y.V. & Roy, J., 2019. *Statistics in medicine,* 38(25), 5048-5069.

BART has several potential advantages over the previous approaches. First, it incorporates covariates into estimates, demonstrating WTP variation across different respondent characteristics. Using MCMC samples, BART evaluates variability in the willingness to pay estimates for each unique combination of specified covariates. Second, it accommodates nonlinear main effects and multiple-way interactions without requiring the researcher to pre-define these relationships (Tan and Roy, 2019). Additionally, the BART model incorporates an estimated choke price, predicting probabilities across the entire range that the researcher specifies. BART can also handle small samples, which is useful when analyzing subsample WTP estimates. Lastly, BART smooths across bid amounts to guarantee that acceptance probability decreases with increasing bids (Follett et al., 2026). While BART has advantages for this application, it does require significantly more computing time than other models.

CHAPTER 8: RESULTS

Implementing the parametric and nonparametric estimation approaches previously mentioned allows for robust analysis of WTP estimates.

Probit Model:

Table 5 displays the definition, mean, standard deviation, and observation count for each covariate, and Table 6 displays the results of the probit regression model.

Table 5: Summary Statistics of Included Variables.

Variable	Definition	Mean	Std. dev.	N
Cost	1 of 7 amounts ranging from \$5 to \$325	119.930	112.850	854
Age	1 of 7 amounts ranging from 21 to 79.50	49.910	16.257	854
Policy Support	=1 if support policies to reduce crowding	0.704	0.457	854
First-time Visitor	=1 if first time visiting Katmai National Park	0.804	0.397	854
Negative Crowding Experience	=1 if number of visitors negatively impacted experience	0.206	0.404	854
Sought Safety Info	=1 if sought out safety information prior to visit	0.545	0.498	854
Day Trip Visitor	=1 if visiting Brooks Camp for one day	0.747	0.435	854
Alaska Resident	=1 if Alaska resident	0.080	0.271	854

Table 6: Probit Regression Results.

Variable	Coefficient	VIF
Intercept	-0.735***	
	(-0.218)	
Cost (US \$)	-0.002***	1.00793
	(<0.001)	
Age	0.007**	1.02817
	(-0.003)	
Policy Support	0.849***	1.04082
	(-0.103)	
First-time Visitor	0.286**	1.11887
	(-0.123)	
Negative Crowding Exeprience	0.288**	1.04303
	(-0.121)	
Sought Safety Information	0.208**	1.02817
	(-0.095)	
Day Trip Visitor	0.031	1.06579
	(-0.111)	
Alaska Resident	-0.096	1.10851
	(-0.181)	

Observations: 841
AIC: 979.90
BIC: 1022.50
McFadden's Pseudo R-Squared: 0.134
Standard errors in parentheses. ** $p < 0.05$, *** $p < 0.01$

First, *Cost* includes one of seven bid amounts ranging from $5 to $325. The *Cost* coefficient is negative and statistically significant in the model, demonstrating that respondents who received a higher bid amount had a lower probability of answering "Yes" to the CV question.

In the survey, we asked respondents to indicate which age category they belonged to. Therefore, *Age* was coded as the midpoint of each categorical response. Ages 18-24 were coded as 21, 25-34 as 29.5, 35-44 as 39.5, 45-54 as 49.5, 55-64 as 59.5, 65-74 as 69.5, and 75 and older as 79.5. To accommodate missing variables for *Age*, the median value replaces all blank responses. The *Age* coefficient is positive and statistically significant at the 5% level, indicating that older respondents have a higher probability of answering "Yes" to the willingness to pay question.

Policy Support is measured by the question "Would you support policies aimed at reducing crowding at Brooks Camp even if it meant it would be more difficult for you to visit the park on a specific day?" The respondents were presented with a Likert scale which included the responses "Strongly Oppose", "Moderately Oppose", "Unsure", "Moderately Support", and "Strongly Support". This was coded as a categorical variable, where the "Moderately Support" and "Strongly Support" responses were coded as 1, and all other responses were coded as 0. *Policy Support* has a coefficient of 0.849 and is statistically significant in the probit model. Those who support policies to limit visitation have a higher probability of answering "Yes" to the willingness to pay scenario, holding all else constant. This coefficient has the largest magnitude of all variables in the model.

First-time Visitor is coded as 1 if the respondent is on their first trip to Katmai National Park in the past 5 years and 0 otherwise. This variable is both positive and significant in the probit model, suggesting that respondents who are on their first visit to Katmai have a higher probability of supporting the reservation system than those who have visited the park previously, holding all else constant.

Negative Crowding Experience is determined by responses to the question "How have the number of visitors contributed to your experience of Brooks Camp?" This question had a Likert scale that respondents could use to answer, which ranged from "Contributed Negatively (1)" to "Contributed Positively (5)". For the probit model, negative responses were coded as 1, and all other responses were coded as 0. *Negative Crowding Experience* is positive and significant in the model, indicating that having a negative experience with the number of people at Brooks Camp increases the probability of a yes-response in the willingness to pay scenario, holding all else constant.

Further, *Sought Safety Info* is coded as 1 if the respondent sought out bear safety information prior to their visit, and 0 otherwise. The coefficient on *Sought Safety Info* is 0.208 and it is statistically significant at the 5% level. Visitors who sought out safety information prior to their visit have a higher probability of a yes-response in the willingness to pay scenario than those who did not, holding all else constant. The final two included variables are insignificant in the probit model. *Day Trip Visitor* is coded as 1 if the respondent was on a one-day trip and 0 otherwise. Lastly, *Alaska Resident* indicates whether respondents live in Alaska, with the variable equaling 1 if the respondent is an Alaska resident and 0 otherwise.

Probit regression results suggest that cost, age, and support for stricter visitation policies, seeking safety information prior to visiting, and having a negative experience with crowding influence the probability of a yes-response. Income was excluded from the empirical model because the income terms cancel out in the theoretical model, suggesting that the respondents' decision to accept or reject the bid amount does not depend on income (Haab and McConnell, 2002).

The probit model estimates a willingness to pay of \$271.71 per person. Using a Krinsky-Robb simulation (Haab and McConnell, 2002), the 95% confidence interval ranges from \$218.78 to \$351.38. This interval reflects moderate uncertainty in the estimated coefficients but suggests that respondents place meaningful value on congestion reduction. When analyzing the probit model's predicted probability curve (Figure 14), it is apparent that this model has wider confidence intervals as the model predicts probability beyond the highest offered bid amount. Moreover, the model predicts that the probability of a yes-response approaches zero when the bid amounts exceed \$1,000.

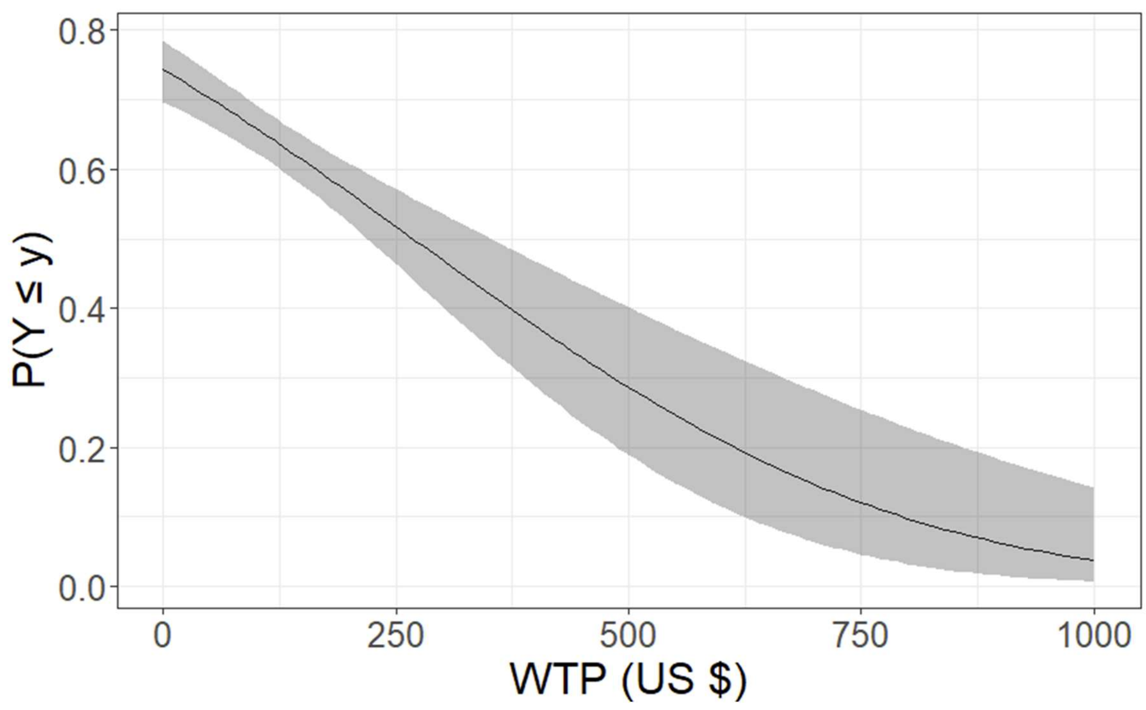

Figure 14: Probit Model Probability Curve.

To evaluate how sensitive WTP estimates are to the assumed functional form for the bid response function, both the linear and log specifications of the *Cost* variable were estimated. The log-cost model estimates a median WTP of $732.92, a mean WTP of $1,275.29, and a 95% confidence interval of $314.26 to $2,149.49. This large shift in the WTP estimate is driven by the choice of functional form. Additionally, the confidence interval for the log specification is asymmetric, suggesting that the simulated WTP values from the Krinsky-Robb draws are skewed. Therefore, the log-cost specification produces a higher and less precise estimate of WTP, reflecting uncertainty in the upper bound. The probability curve predicted by the log specification of the probit model is shown in Figure 15.

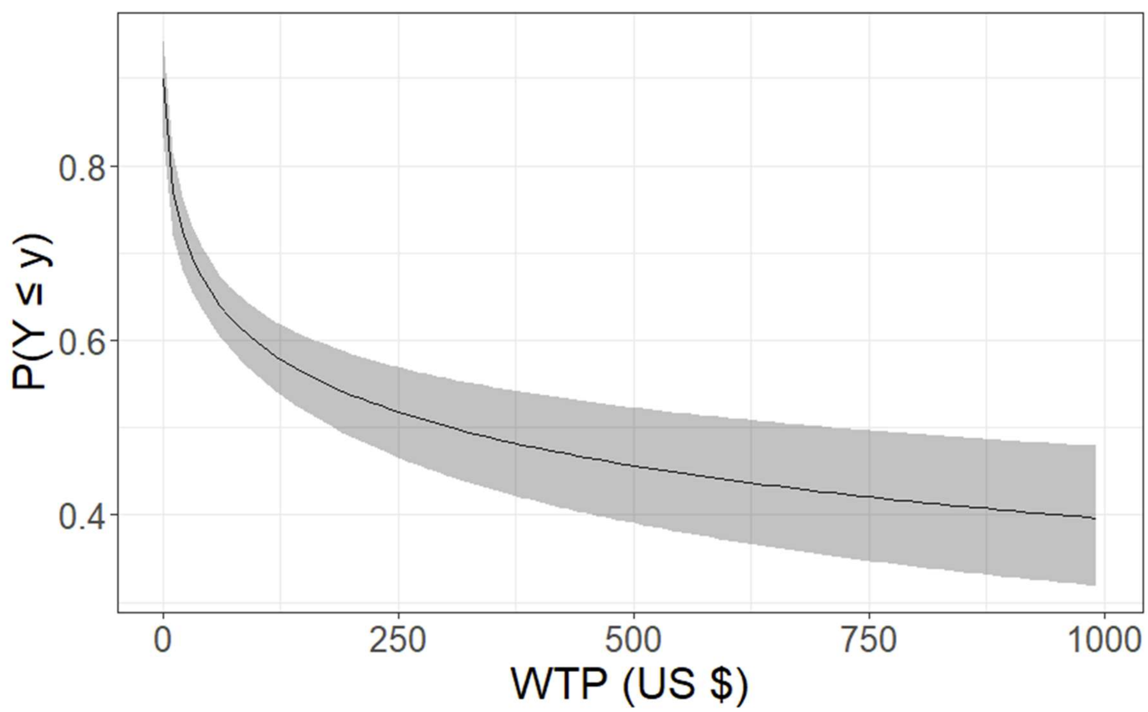

Figure 15: Log-Cost Specification Probit Model Probability Curve.

Wilde (2008) recommends testing the normality assumption of the probit model since the maximum likelihood of the probit model is biased for nonnormal disturbances. Wilde implements the Bera-Jarque-Lee test used by Bera et al. (1984) which has a null hypothesis of normally distributed residuals. When applied to the linear probit model, the test statistic is

13.393 and the p-value is 0.0012. We reject the null hypothesis at the 1% significance level, indicating that the residuals are not normally distributed as the probit model assumes.

In addition to the bid-response function exhibiting non-monotonicity and the absence of a clear choke price, the probit model's distributional assumption appears to be violated. Therefore, nonparametric models which do not impose functional form assumptions on the data may be more appropriate. Figure 16 shows the predicted probability curve of the BART model with the Kriström adjustment choke price of $878.58. This curve differs substantially from that of the linear and log probit models; however, it is like the Bayesian probit model. The BART model constructed 200 trees, discarding the first 5,000 posterior draws and saving the second 5,000 posterior draws. Moreover, a monotonicity adjustment using the pool adjacent violators algorithm (PAVA) is applied to each posterior draw to enforce the requirement that acceptance probabilities decline with increasing bid amounts. For the Bayesian probit model, we run four parallel MCMC chains for 2,000 iterations each. We discard the first 1,000 and retain the remaining 1,000 draws from each chain, resulting in 4,000 total posterior draws. The intercept and coefficient are assigned weakly informative independent normal priors (Follett et al., 2026).

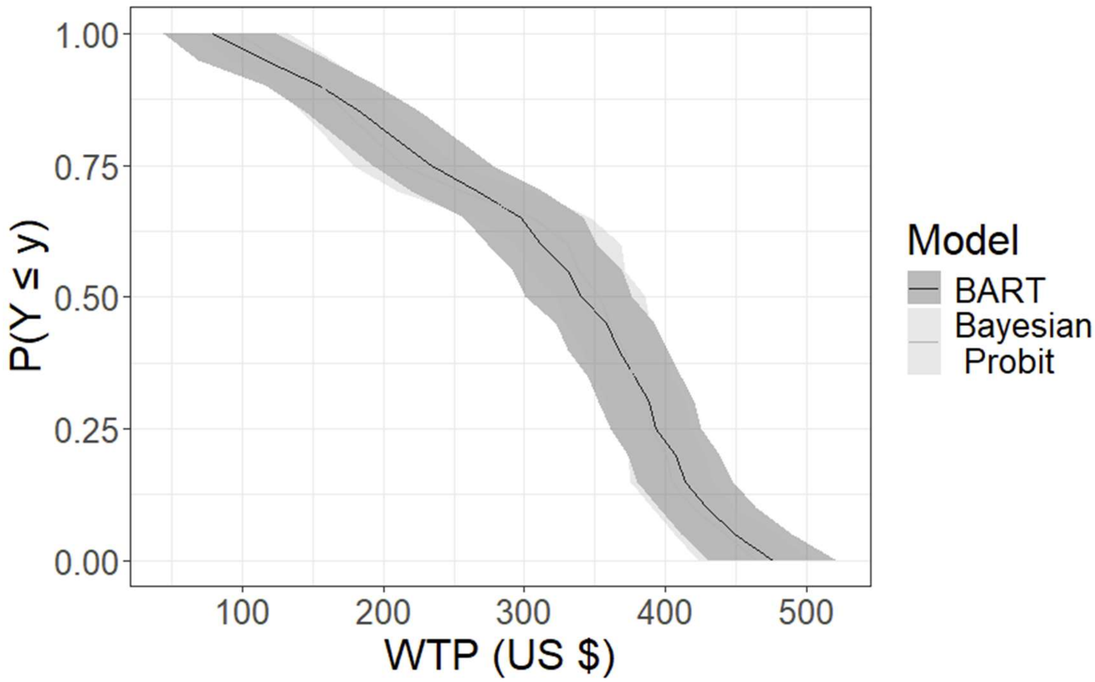

Figure 16: BART and Bayesian Probit Models Probability Curve.

Figure 17 shows results from the Turnbull, Probit, Bayesian Probit, Kriström, Kriström adjustment, and BART models.

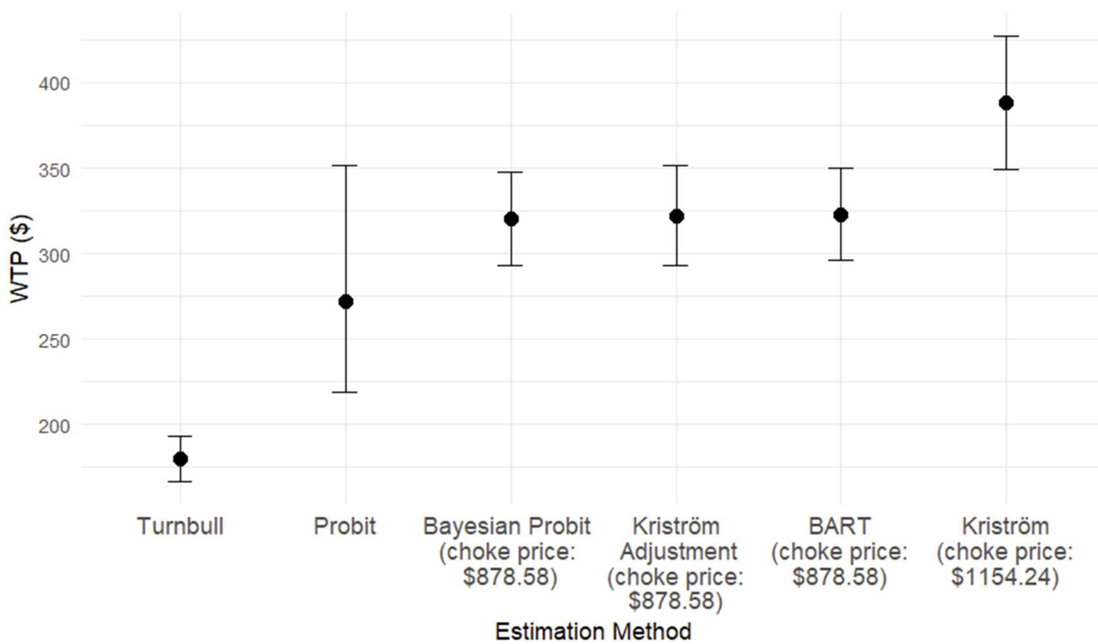

Figure 17: Sensitivity Analysis of Willingness to Pay Estimates.

The Turnbull provides a lower bound estimate of $179.93. The Kriström model offers an upper bound estimate of $388.29. This model estimates a choke price of $1,154.24 using interpolation between the two highest bids. The Kriström adjustment estimates a choke price of $878.58 by interpolating across the entire bid range, estimating WTP to be $322.21. With the Kriström-adjusted upper bound, the Bayesian probit estimates mean WTP of $320.33 and the BART produces an estimate of $323.94. When specifying the same choke price, the Kriström, Bayesian probit, and BART models produce nearly identical estimates. This is further explored across varying upper bound specifications.

The sensitivity analysis reveals that estimates are driven in part by assumptions about the upper bound. While the Turnbull estimator truncates estimates at $325, the Kriström assumes a substantially higher upper bound of $1,154.24. The BART, Bayesian probit, and Kriström-adjusted estimates converge in part because both use the same choke price of $878.58. This Kriström-adjusted choke price is reasonable by acknowledging that many respondents' willingness to pay extends beyond $325, while also recognizing that a flat slope at the right-tail of the bid distribution results in a very high choke price in the Kriström model. Therefore, $322 is a realistic central estimate of willingness to pay. Ultimately, the combination of nonparametric approaches provides a range of plausible welfare estimates, with the true mean likely lying between the Kriström and Turnbull estimates. This bracketing approach realizes uncertainty while providing relevant guidance to policymakers and park managers.

CHAPTER 9: DISCUSSION

The Kriström, Bayesian Additive Regression Trees, and Bayesian probit offer estimates within a $3.61 range when an upper bound of $878.58 is defined. These estimates represent the average amount that visitors would pay to reduce wait times to 15 minutes or less and to ensure unobstructed views on the Falls platform. Across three upper bound specifications, the BART and Kriström models produce very similar WTP estimates (Table 7). This finding suggests further research is necessary to address under which conditions the BART and Kriström models either diverge or validate one another (Follett et al., 2026, found very different estimates using a different data set).

Table 7: Kriström, BART, and Bayesian Probit Estimates across Upper Bound Specifications

Choke Price	Kriström	BART	Bayesian Probit
$326 (Highest Bid + $1)	189.74	188.52	193.90
	[144.00, 235.48]	[177.35, 199.44]	[183.30, 204.39]
$878.58 (Kriström Adjusted Upper Bound)	322.21	323.94	320.33
	[293.20, 351.21]	[297.6, 349.68]	[292.81, 347.78]
$1,154.24 (Kriström Upper Bound)	388.29	391.81	383.10
	[349.13, 427.46]	[356.83, 424.56]	[346.74, 420.39]

The Kriström, BART, and Bayesian probit 95% confidence intervals are also reported in Table 7. For all three estimates, the BART model produces similar, yet tighter confidence intervals than the Kriström model for the $878.58 and $1,154.24 upper bounds. For the choke price of $326, the BART model has a much tighter confidence interval, indicating a more precise and reliable estimate in this scenario.

Variable importance is assessed using variable inclusion proportions, which track the average frequency with which each predictor is used as a splitting variable across posterior draws, following Chipman et al. (2010). This number demonstrates the probability that a variable is included in the model in a meaningful way, measured through variable splitting frequency across all posterior draws. *Cost* has a probability of 0.686, indicating that in 68.6% of posterior samples, *Cost* was used as a splitting variable. *Age* has a probability of 0.570, indicating that it is the second strongest predictor in the BART model. *First-time Visitor* has a probability of 0.420, demonstrating moderate evidence of prediction in the model. *Policy Support* and *Negative Crowding Experience* have probabilities of 0.389 and 0.345 respectively, showing that these variables are weaker predictors of WTP yet still present in the model. Following Bleich et al. (2014), inclusion proportions are compared against a null threshold of 1 divided by the number of covariates (in our case, 0.20). All five variables meaningfully contribute to splitting since each probability exceeds 0.20. However, *Cost* and *Age* are the only variables that have a probability exceeding 0.50, being the only covariates to show strong and consistent inclusion, suggesting they play a primary role in explaining bid acceptance.

Chipman et al. (2010) uses partial dependence plots functions to examine the marginal relationship between each covariate and outcome variable. This fixes the covariate at a given value and averages the predicted WTP across the full empirical distribution of other covariates. These functions make no assumption about the functional form of the relationship between covariates and WTP. This allows for nonlinear and interactive effects to be captured and summarized as a marginal effect curve. Figure 18 displays the partial dependence plots for the four covariates included in the BART model.

Age shows a positive relationship with WTP, with predicted WTP generally increasing across the observed age range. Respondents younger than 40 years old exhibit higher average WTP than visitors over the age of 60. *First-time Visitor* shows that repeat visitors exhibit lower predicted WTP compared to first-time visitors. *Policy Support* demonstrates that respondents who expressed support for policies which limit visitation have higher predicted WTP than those who did not. Lastly, *Negative Crowding Experience* shows that respondents who reported a negative experience with crowding have higher predicted WTP compared to those with neutral or positive experiences.

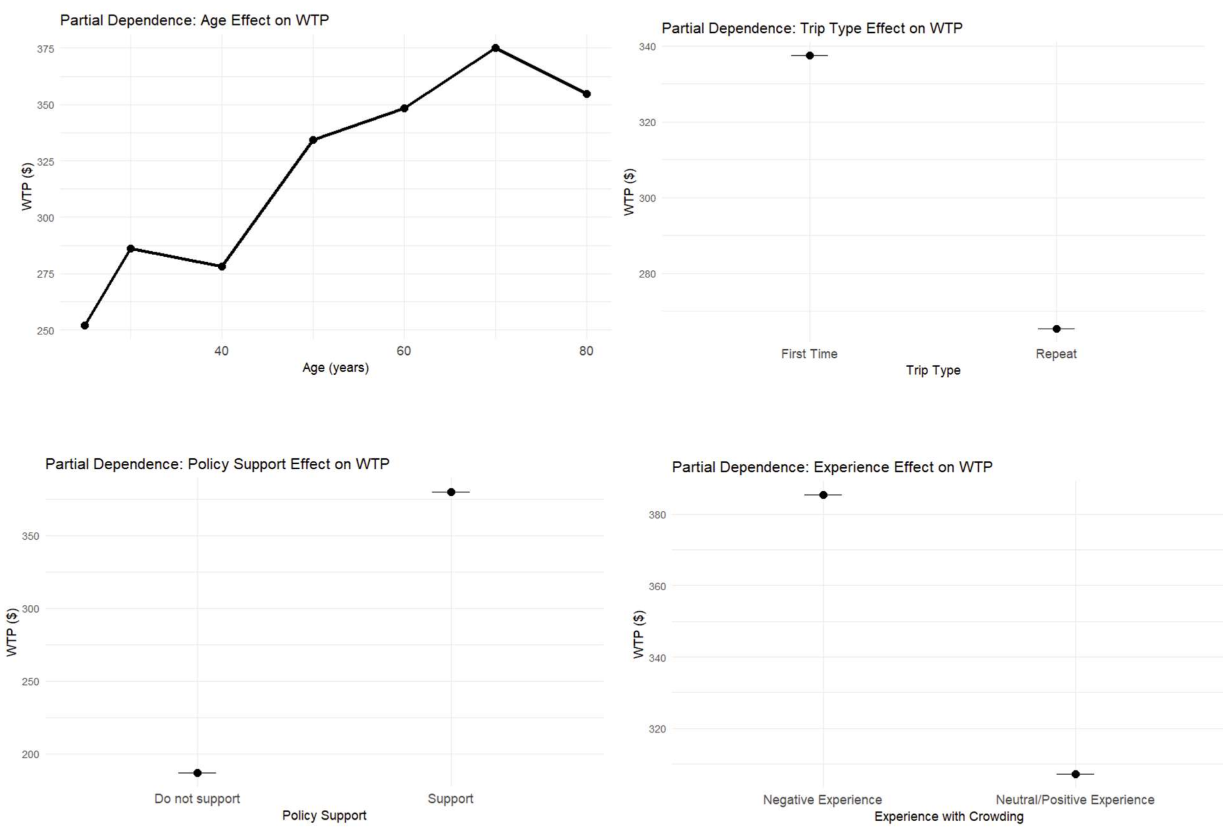

Figure 18: Partial Dependence Plots for BART covariates.

A notable outcome from Figure 18 is that respondents who support policies which reduce crowding at Brooks Camp, even if they make it more difficult for the respondent to visit the park on a specific day, have a higher estimated WTP in the BART model. One limitation of the survey, discussed in the following section, is that the contingent valuation question did not mention the tradeoff that a reservation system can reduce visitors' access to the park on specific days. To address this limitation, we remove any respondent who stated that they would not support policies which reduce crowding even if it makes it more difficult for them to visit the park on a specific day, but then later accepted the bid amount in the CV scenario. Removing these inconsistent responses takes 94 respondents out of our survey. The bid-response function is depicted in Figure 19, showing that there are lower acceptance rates at each bid amount when inconsistent responses are excluded from the sample.

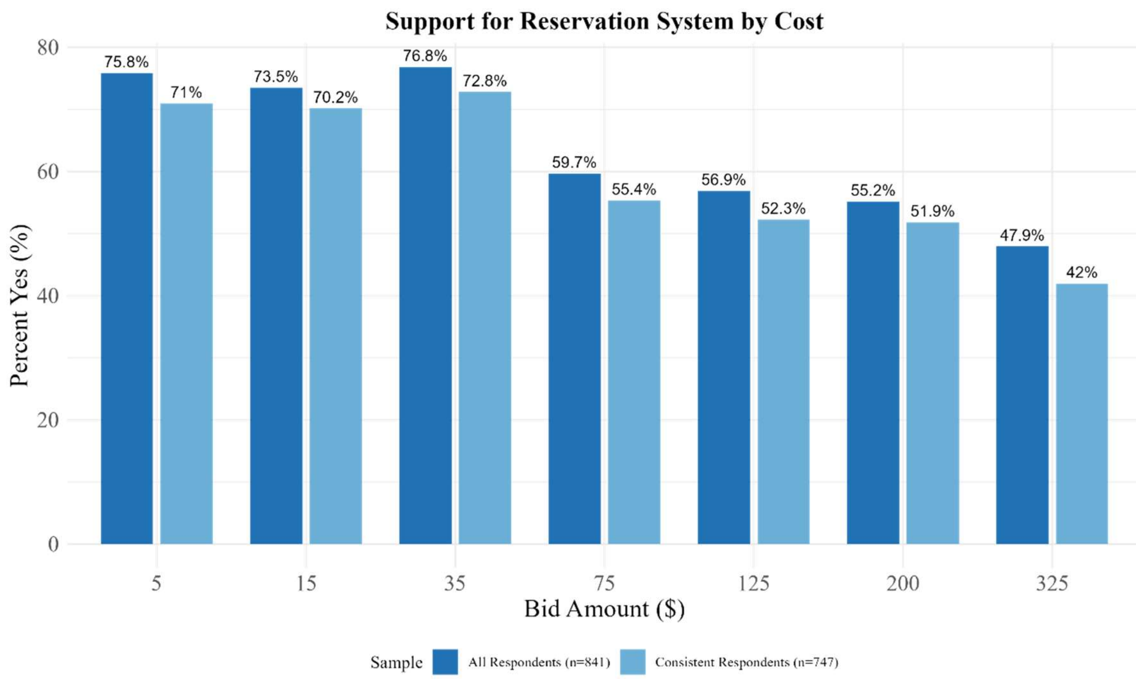

Figure 19: Percent of Yes-Responses to Contingent Valuation Question (Comparing All Respondents to Respondents With a Consistent Response to *Policy Support*)

The WTP estimates from the full sample and the consistent sample across the Kriström, Kriström adjustment, BART, and Bayesian probit models, are reported in Table 8.

Table 8: Willingness to Pay Estimates (All Respondents vs. Consistent Responses)

Specification	Kriström	Kriström Adjustment	BART	Bayesian Probit
All Responses (N = 841)	388.29	322.21	323.94	320.33
	[349.13, 427.46]	[293.20, 351.21]	[297.6, 349.68]	[292.81, 347.78]
Consistent Responses (N = 747)	288.89	264.1	258.98	258.42
	[246.78, 331.00]	[239.30, 288.90]	[235.70, 281.52]	[233.80, 283.70]

For the consistent response sample, the Kriström estimates a choke price of $856.88, while the Kriström adjustment estimates a choke price of $738.81. Lower acceptance rates cause the WTP distribution for the consistent sample to have a less severe fat and flat tail, leading to lower choke price estimates. Removing the 94 inconsistent responses from our WTP sample reduces individual WTP estimates. The WTP estimate for consistent respondents is $99.40 lower with the Kriström model, $58.11 lower with the Kriström adjustment, $64.96 lower with the BART model, and $61.91 lower with the Bayesian probit model. Like Table 7, we specified the Kriström adjustment choke price to be the upper bound in the BART and Bayesian probit models. Ultimately, this analysis allows us to report more conservative estimates in addition to our full-sample WTP estimates.

CHAPTER 10: LIMITATIONS AND CONCLUSION

Limitations

While this study provides the first direct estimates of visitors' willingness to pay for congestion reduction at Brooks Camp, there are several limitations of the study. First, the contingent valuation approach relies on stated preferences in a hypothetical scenario. Hypothetical bias is a relevant concern, although there are several factors in this study which mitigate this concern. The scenario described realistic policy changes with tangible changes rather than abstract improvements. Also, respondents were asked about the trip they are currently on, making costs and benefits of their visit salient and realistic.

Second, the CV question did not explicitly state that a reservation system would reduce visitors' ability to access Brooks Camp on specific dates due to a capacity quota. While a previous question in the survey addressed this concept by asking respondents, "would you support policies aimed at limiting visitation even if it made it more difficult for you to visit the park on a specific day", the CV question did not mention this tradeoff. Respondents may have focused on the benefits of reduced crowding without fully understanding the associated costs. This could bias estimates upwards as respondents may have answered "no" if the probability of being unable to secure a reservation was clearer. This limitation is addressed in the discussion section and conservative estimates are provided.

Similarly, the CV question stated a reservation system would result in an "$X increase in personal trip costs." For respondents travelling in groups, it may have been unclear whether this fee would increase each person's trip cost or the entire group's trip cost by the offered bid amount. This may have been particularly unclear for parents who paid for their entire family to visit. This may have biased results to the willingness to pay question.

Moreover, the dichotomous choice format avoids anchoring effects, however it only captures whether WTP exceeds each bid amount, not the magnitude of the difference. This reduces statistical efficiency and provides limited information about the upper tail of the WTP distribution (Johnston et al., 2017). Additionally, travelling to Brooks Camp is often a “bucket list” trip for many people. Most respondents were on their first visit to Katmai National Park. This may impact WTP estimates if people are not planning to visit Brooks Camp again; their response to the CV question may not accurately reflect their real-world behavior.

There are also limitations of the survey administration in this study. Data were collected over 12 days corresponding with peak visitation; however, this window may not fully capture the variation in visitor types, crowding experiences, bear behavior, or tolerance for congestion across the visitation season. Ultimately, it was important to capture visitor perceptions at the busiest points of the season to understand the true impacts of crowding. In addition, surveys were also administered primarily at the Treehouse platform. This location could oversample visitors most affected by crowding while visitors who arrived during less crowded periods could be underrepresented. This sample selection could bias WTP estimates upward if those most negatively affected by congestion are overrepresented. However, this could also bias estimates downward if those who self-selected out due to low tolerance for crowding are excluded. Future studies should aim to collect surveys during off-hours, when those with lower tolerances for crowding are on the platforms.

Further, a common issue in intercept surveys is nonresponse bias. Even though we intercepted nearly all visitors we encountered, there is potential for nonresponse bias, for instance if those who refused to take the survey have systematically different willingness to pay than those who agreed to take the survey.

Several factors relevant to reservation systems are omitted from this analysis. First, this study does not examine how reservations should be allocated. Second, this paper does not analyze distributional impacts across visitor groups. Moreover, spillover effects are not included in the study. However, it is important to consider where visitors will travel if they do not get a reservation at Brooks Camp. If they substitute for other locations in Katmai National Park, congestion could become a relevant issue at nearby sites. Finally, this paper focuses exclusively on visitor welfare, without considering ecological impacts, implications for NPS staff, or effects on local tour operators and communities. A complete welfare analysis should incorporate these dimensions.

Lastly, Brooks Camp presents a unique recreation experience with remoteness, high travel costs, strict spatial constraints, iconic wildlife viewing, and viral social media presence. While these features make it an ideal setting for studying congestion in constrained spaces, the results have limited generalizability. Visitors to Brooks Camp represent a high-income and motivated population. WTP estimates from this sample cannot be directly applied to more accessible parks with more diverse visitor demographics. Despite this, visitor experiences and management preferences are likely to extend to other settings. While the WTP estimate is dependent on-site context, the preferences can inform management at similar high-value, spatially limited sites.

Conclusion

The congestion problem in national parks is increasing and needs to be addressed. The high acceptance of reservation fees signals to the National Park Service that visitors care about crowding during their visit and support management changes. With 70% of respondents supporting policies which limit visitation, there is strong support for less crowding. The mean willingness to pay was $323.94 for reduced congestion, using the BART model with the Kriström-adjusted choke price. This reveals that visitors place a high value on congestion reduction in part due to the fact that they are already incurring high travel costs to visit Brooks Camp. For a "bucket list" destination like Katmai National Park, reservation fees are justified by improvements in the visitor experience. Additionally, long wait times represent a large amount of visitors' time in the park, particularly for those on a day trip.

The WTP estimates are interpreted as compensating variation for an improved visitor experience. These estimates can inform welfare implications of a reservation system at Brooks Camp. WTP estimates are expected to be large given the relatively high percent-yes responses across all bids. When compared to visitors' total trip expenditures, these estimates represent only a marginal increase in total travel costs. According to NPS estimates, each visitor to Katmai spends approximately $1,946 on their visit (National Park Service, 2024b). Therefore, a bid amount of $325 represents around fifteen percent of total travel costs. Future research should include higher bid amounts to more accurately measure the upper bound of visitor WTP.

Moreover, this survey only captured people who actually visited the park, so we lack data on people who intend to visit the park. This creates the opportunity for a survey to be conducted on explore.org regarding intended visitation. Further, at Brooks Camp, congestion creates complex safety tradeoffs as larger groups may increase feelings of safety for some visitors while increased human-wildlife interactions caused by crowding may reduce safety perceptions for others. This dynamic should be further explored to inform an analysis of the optimal number of visitors per day.

This pilot study provides estimates of visitors' willingness to pay for congestion reductions at Brooks Camp and the first direct valuation of a reservation system in a national park. Results indicate that visitors value improvements in crowding conditions, with positive willingness to pay for a reservation system that reduces wait times and improves viewing experiences. The findings offer tangible guidance for park managers while highlighting important areas for future research, offering broader implications beyond Katmai. As more parks face rising visitation and spatial constraints, understanding the welfare implications of park management policies is critical for balancing access and visitor experience.

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APPENDIX A: SURVEY INSTRUMENT

Survey Details

This section is for researcher use only.

Researcher:

Location:

- ○ Treehouse
- ○ Brooks Lodge
- ○ Lower River
- ○ Campground
- ○ Other

Weather

- ☐ Rainy
- ☐ Windy
- ☐ Planes not landing/taking off
- ☐ Planes landing on Brooks Lake (east wind)
- ☐ Sunny

Are there any other notes you would like to add to this record

Intro

Colorado State University is conducting a study of wildlife tourism in Katmai National Park. This visitor survey project has been issued Research and Collecting Permit KATM-2025-SCI-0005 by Katmai National Park, but has received no funding from the National Park Service. **The following survey asks a series of questions about your experience at Brooks Camp in Katmai National Park.** For the purposes of this survey, "Brooks Camp" refers to the area surrounding Brooks River including the lodge, campground, roads, trails, and wildlife-viewing platforms. We are very interested in your opinions. Your responses are confidential and anonymous. Thank you very much for participating!

Visit

Please tell us a bit about your visit to Katmai National Park.

How many times have you visited Katmai National Park in the last five years? (including this visit)

- ○ 1 visit - this is my first time here
- ○ 2 visits
- ○ 3 visits
- ○ 4 visits
- ○ 5 visits
- ○ ______ If more than five visits, please enter number of visits

Are you currently on a day trip to Brooks Camp?

- ○ Yes
- ○ No

Did you know you would be coming specifically to Brooks Camp when you decided to take a bear viewing or fishing trip?

- ○ Yes, I knew I was coming to Brooks Camp.
- ○ No, I did not know where the guide would be bringing us.

Did you enter the housing lottery for Brooks Lodge for this year?

- ○ Yes
- ○ No

How many nights do you plan to spend at Brooks Camp?

- ○ 1 night
- ○ 2 nights
- ○ 3 nights
- ○ 4 nights
- ○ 5 nights
- ○ 6 nights
- ○ 7 nights
- ○ ________ If more than 7 nights, please enter how many nights

Where are you staying during this trip to Brooks Camp?

- ☐ Brooks Camp Campground
- ☐ Brooks Lodge
- ☐ ________ Other

Including yourself, how many people are in your personal group during this visit to Brooks Camp?

- 1 (just me)
- 2
- 3
- 4
- 5
- ______ If more than five people, please enter how many

Which activities do you plan to do during your visit to Brooks Camp? Please check all that apply.

- bear watching
- fishing
- photography
- river walk
- Valley of Ten Thousand Smokes
- hike Dumpling Mountain
- ______ other (please specify)

Bears

Approximately how many bears have you seen so far today?

- 0 bears
- 1 - 5 bears
- 6 - 10 bears
- 11 - 20 bears
- More than 20 bears

During this trip, approximately how many different individual bears were you able to identify/recognize either by number, nickname, physical characteristics, and/or behavior?

- 0 bears

- 1 bear
- 2 - 4 bears
- 5 - 7 bears
- More than 7 bears

Did you know that many of these bears have been identified with numbers and sometimes nicknames?

- Yes
- No

Did you come here to try to see a particular bear(s)?

- Yes
- No

Please indicate your level of agreement with the following statements.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree	Not applicable
The ability to see specific individual bears influenced my decision to visit Brooks Camp	O	O	O	O	O	O
The ability to watch specific individual bears enhanced the quality of my visit to Brooks Camp	O	O	O	O	O	O

Knowledge

How safe do you feel walking the trails to and from the viewing platforms?

Not at all safe (1)	(2)	(3)	(4)	Very safe (5)
○	○	○	○	○

Did you actively seek out information about brown bear safety before this trip to Brooks Camp?

- ○ Yes
- ○ No

Where did you seek your brown bear safety information? (Please check all that apply.)

- ☐ Printed materials (e.g., pamphlets/brochures, newspapers/magazines, guide books, etc.)
- ☐ Family/friends
- ☐ Private company tour guide
- ☐ Internet (e.g., websites or social media such as Facebook, etc.)
- ☐ Video (e.g., documentaries, movies, TV shows, news programs, etc.)
- ☐ ________ Other (please specify)

Which of the following describe(s) your reason(s) for not seeking out information?

- ☐ I don't think it is unsafe.
- ☐ I don't know where to get information.
- ☐ I knew I would be going to bear school when I arrived at Brooks Camp.
- ☐ I got information before past trips, but did not seek new information for this trip.
- ☐ I already have a lot of knowledge from recreating or living in brown bear country.
- ☐ ________ Other (please specify)

Bear Viewing

Please tell us about your bear viewing experience.

How many times have you been on the Brooks Falls bear viewing platform during this trip?

- 0
- 1
- 2
- ______ 3 + (please specify)

When did you most recently visit the Brooks Falls bear-viewing platform on this trip?

- Today
- Yesterday
- ______ Other (please specify)

What is the longest amount of time you have waited to get on the Brooks Falls platform during this trip?

- No wait time
- Less than 15 minutes
- 15 - 30 minutes
- More than 30 minutes but less than 1 hour
- 1 - 2 hours
- ______ More than 2 hours (please specify)

Are you currently on the waitlist for the Brooks Falls bear viewing platform?

- Yes
- No

How long do you expect to wait today to get on the Brooks Falls platform?

- Less than 15 minutes
- 15-30 minutes
- More than 30 minutes but less than 1 hour
- 1 - 2 hours
- ____ More than 2 hours (please specify)

In your opinion, what is the longest amount of time a visitor should be expected to wait to get on the Brooks Falls platform?

- No wait time
- No more than 15 minutes
- No more than 30 minutes
- No more than 1 hour
- No more than 90 minutes
- No more than 2 hours

Crowding

Next, we would like to know a bit more about your experiences at Brooks Camp.

How have each of the following contributed to your experience at Brooks Camp?

	Contributed Negatively (1)	(2)	Neither Positive nor Negative (3)	(4)	Contributed Positively (5)
Number of bears	○	○	○	○	○
Number of visitors	○	○	○	○	○
Variety of places to view bears	○	○	○	○	○
Bear school orientation	○	○	○	○	○
Wait time to get on platform	○	○	○	○	○

	Contributed Negatively (1)	(2)	Neither Positive nor Negative (3)	(4)	Contributed Positively (5)
Interactions with rangers	○	○	○	○	○
Number of people on the platforms	○	○	○	○	○

Over the past 15 years, Brooks Camp has seen dramatic increases in visitation. Recently, there have been numerous periods when the number of visitors was close to or exceeded the ability of the park to comfortably accomodate them. Lodging and camping reservations can be very difficult to secure, access to the viewing platforms often requires long wait times, and the viewing platforms can become crowded during the peak visitation season.

Please indicate your level of agreement with the following statement. If crowding continued to increase above current levels, I would be less likely to visit Brooks Camp in the future.

Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
○	○	○	○	○

To address issues of crowding, Katmai National Park could potentially adopt policies to manage the number of visitors allowed at Brooks Camp each day.

Would you support policies aimed at reducing crowding at Brooks Camp even if it meant it would be more difficult for you to visit the park on a specific day?

No Strongly Oppose (1)	No Moderately Oppose (2)	Unsure (3)	Yes Moderately Support (4)	Yes Strongly Support (5)
○	○	○	○	○

Which option to reduce congestion and crowding at Brooks Camp would you most prefer?

- Reduce the number of people staying overnight in the campground and lodge
- Limit the number of people visiting just for the day
- ________ Other (Please specify)
- There is no need to reduce crowding/congestion

Should the number of people allowed to visit Brooks Camp each day be limited if it is needed for any of the following reasons, even if it limits when you can visit? (Check one box for each reason.)

	Yes	No	Don't Know/Not Sure
To protect the quality of visitors' experiences	○	○	○
To protect visitors' safety	○	○	○
To reduce environmental impacts	○	○	○
To protect brown bears and other wild animals	○	○	○

The Brooks Falls bear viewing platform holds a maximum of 40 people. When the platform is full, people are limited to 30 minutes of time on the platform and park rangers manage a waitlist.

What should rangers prioritize when managing visitors on the platform?

Click and drag the items below to rank them from 1 (most important) to 3 (least important).

Keeping the wait time as short as possible

Making sure the platform isn't too crowded

Allowing visitors plenty of time on the platform

There are potentially different ways to provide access to the Platform. Which scenario would you **most** prefer?

Capacity: 40 people **Time limit:** 30 mins **Wait time:** Unchanged	**Capacity:** 40 people **Time limit:** 20 mins **Wait time:** Decreased	**Capacity:** 30 people **Time limit:** 30 mins **Wait time:** Increased	**Capacity:** 30 people **Time limit:** 20 mins **Wait time:** Unchanged
○	○	○	○

Currently, access to Brooks Camp does not require a reservation. However, a reservation system could be implemented to reduce crowding and reduce the wait time to access the Brooks Falls viewing platform. The benefit of a reservation system would be that there would be fewer people at Brooks Camp each day. Visitors could expect wait times of 15 minutes or less to get on the platform and visitors would have unobstructed views of the bears and river when on the platform.

Considering the benefits of less crowding, would you support such a reservation system even if it meant your personal costs for this most recent trip to Brooks Camp were $${e://Field/cost} higher than the total amount you paid for this trip?

○ Yes

○ No

Which of the following **best** describes why you would not support this system.

○ I cannot afford it.

○ ______ I cannot pay that amount, but I would pay

○ I do not think there should be a reservation system.

○ I think there should be a reservation system, but it should be free

○ I do not think Brooks Camp is too crowded.

○ ______ Other (please specify)

Webcams

Next we would like to ask you about your experience with the webcams (bearcams) at Brooks River.

Before you left your home for this trip, did you know that you could watch these bears live online at websites such as Explore.org and YouTube?

- Yes
- No

Have you watched these live webcams (bearcams)?

- Yes
- No

Based on your webcam (bearcam) viewing experience, please indicate your level of agreement with the following statements.

Watching the webcams (bearcams) ...

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree	Not applicable
Helped me understand the behavior of the bears that I saw on this visit	O	O	O	O	O	O
Helped me recognize some of the individual brown bears that I saw on this visit	O	O	O	O	O	O
Helped me learn when and where to watch bears at Brooks River	O	O	O	O	O	O

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree	Not applicable
Contributed to my decision to visit the Park	○	○	○	○	○	○

Have you heard of Fat Bear Week?

○ Yes
○ No

Participant Info

In this final section of the survey, please tell us a little bit about yourself.

In which country do you currently reside?

Please specify your country of residence

What is your Zip Code (5-digit)?

What is your sex?

○ Female
○ Male

○ I prefer not to answer

What is your current age?

Which of the following best describes your employment status?

○ Full-time salaried
○ Full-time hourly
○ Part time
○ Self-employed
○ Retired
○ Unemployed
○ Other

What is your household size (including you)?

What is the highest degree of schooling you have attained?

Which of these categories best represents your annual household income (U.S. dollars)?

Including yourself, how many people contribute to your annual household income?

○ 1

○ 2
○ 3
○ [ ] 4 or more (please specify)

Thank you very much for your time! Is there anything else you would like to tell us?

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APPENDIX B: ADDITIONAL SURVEY QUESTION RESPONSES

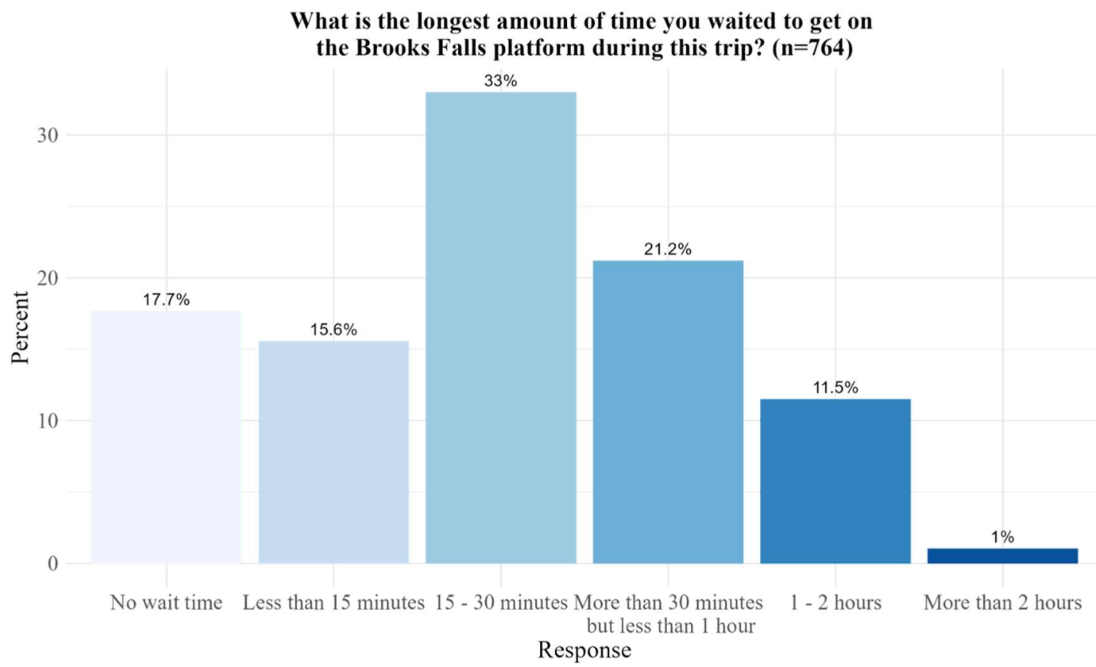

Figure 20: Experienced Wait Times for Falls Platform.

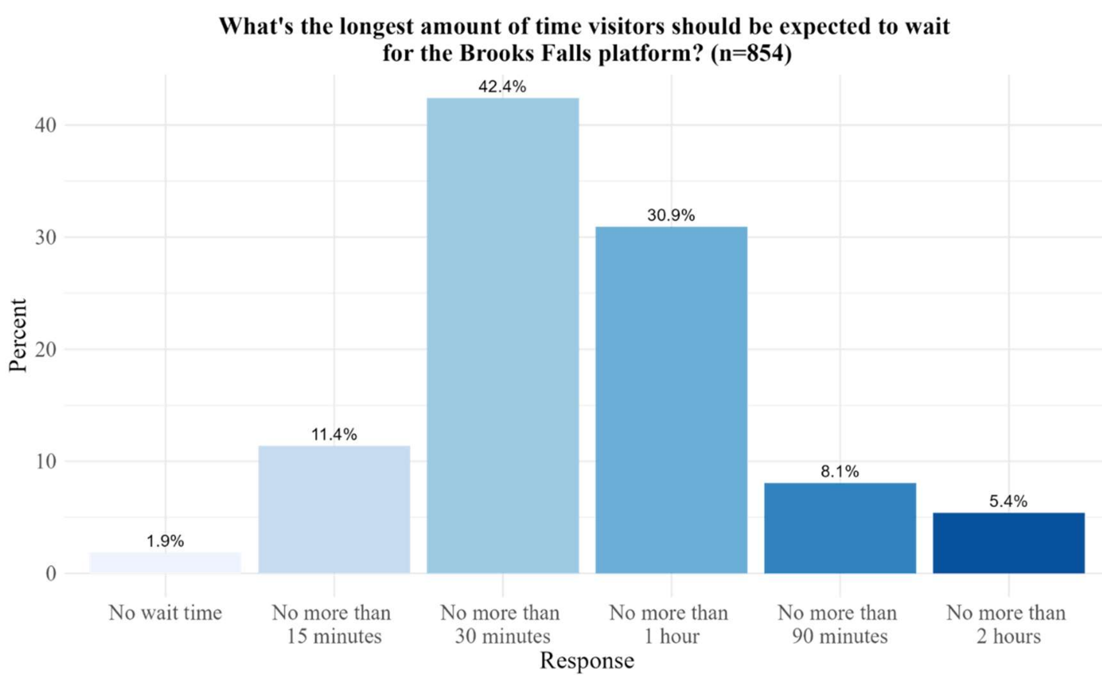

Figure 21: Preferences for Wait Times for the Falls Platform.

APPENDIX C: RESPONSES SPLIT BY DAY TRIP AND OVERNIGHT TRIP VISITORS

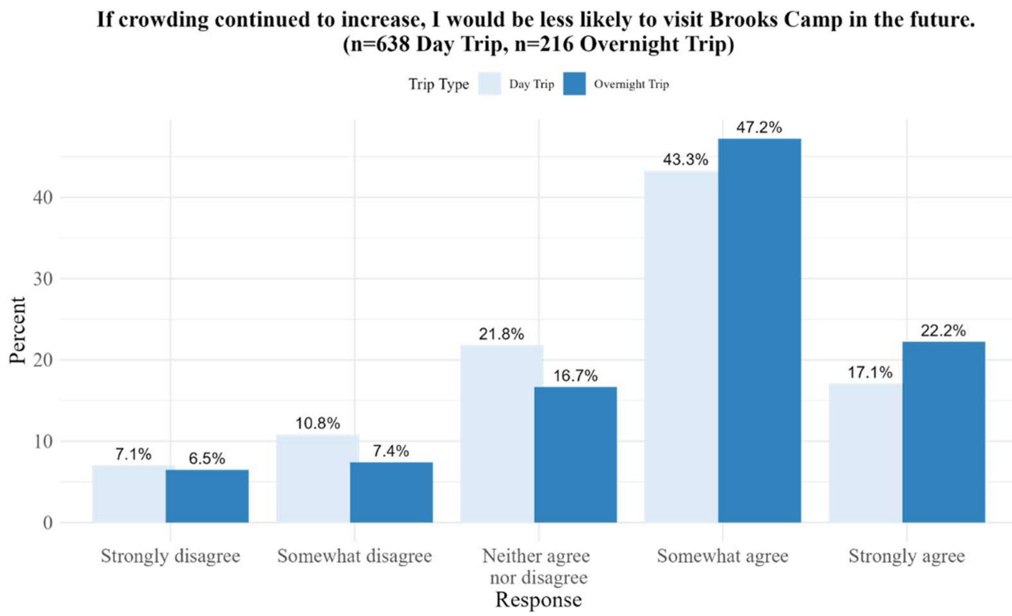

Figure 22: Impact of Crowding on Future Visitation (Comparing Day Trip Respondents and Overnight Trip Respondents).

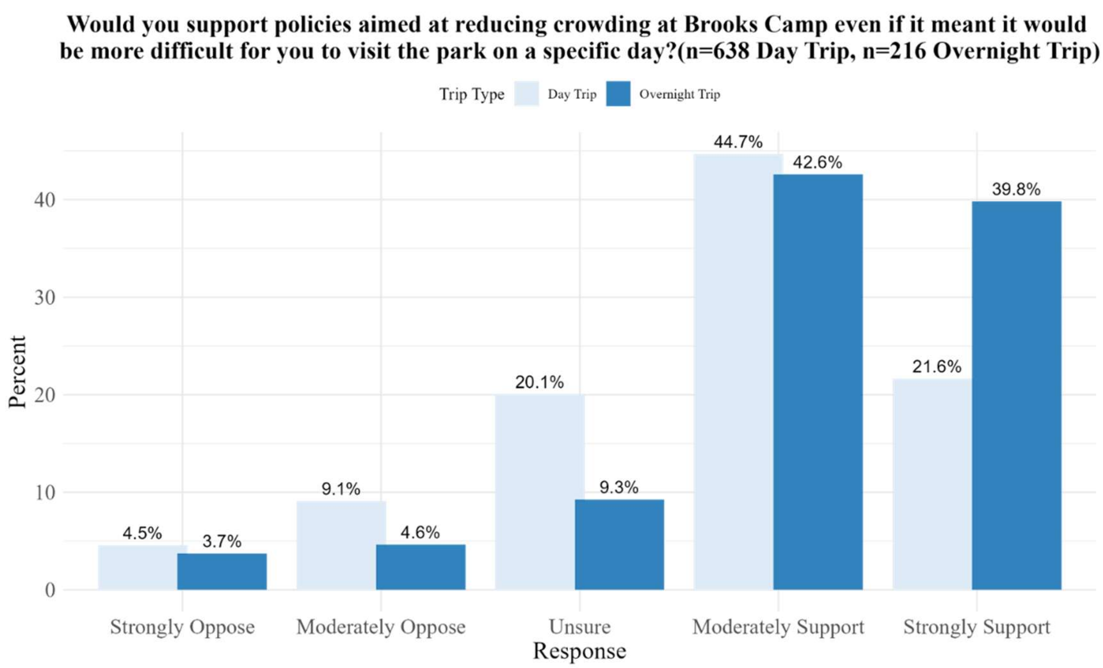

Figure 23: Support for Policies which Reduce Crowding (Comparing Day Trip Respondents and Overnight Trip Respondents).

APPENDIX D: RESULTS WITH PROTESTS EXCLUDED

Protests are identified in our willingness to pay questions with the follow up question which asks respondents who answered “no” why they responded this way. We identified the response “I think there should be a reservation system, but it should be free” as a protest response because respondents might be capable of paying the reservation fee, but they do not think they should have to pay for it. In total, 113 respondents are classified as protest respondents, leaving 728 observations in our WTP sample. Figure 24 shows the bid-response function when respondents who answered “I think there should be a reservation system, but it should be free” are excluded from the analysis. There are higher yes-response rates at each bid.

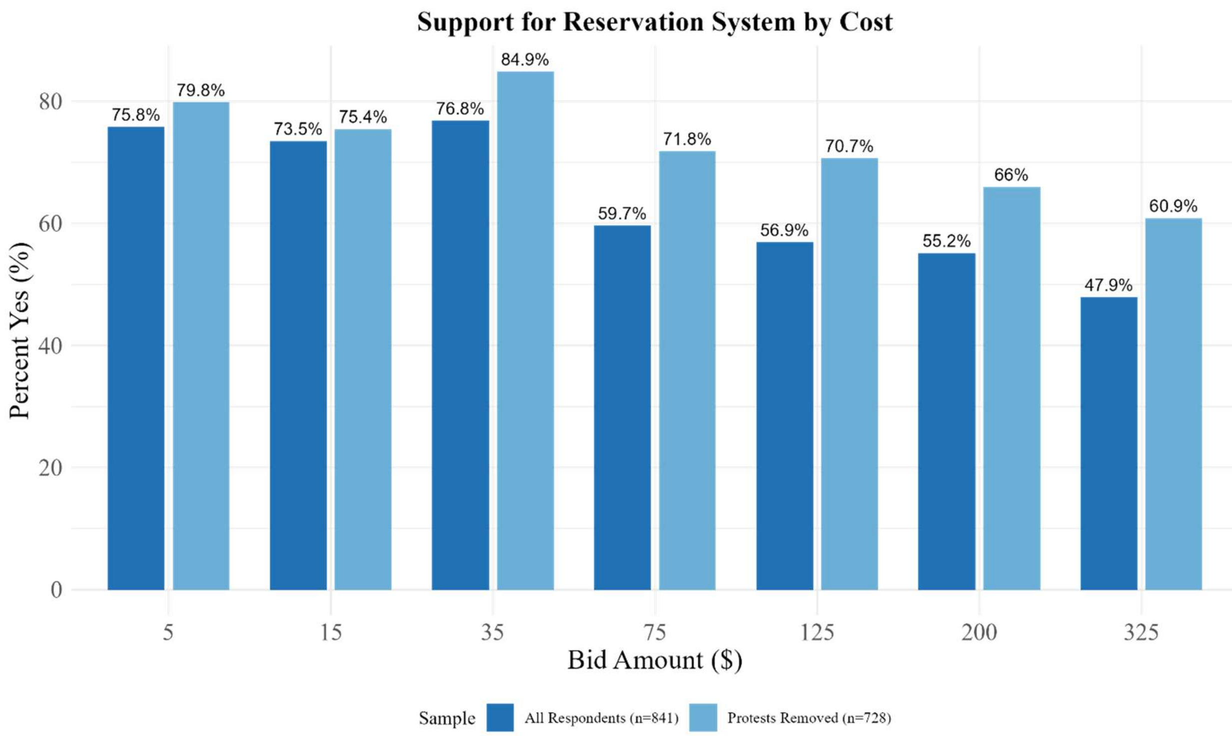

Figure 24: Percent of Yes-Responses to Contingent Valuation Question (Protests Excluded)

Figure 25 shows a comparison of willingness to pay estimates from the whole sample compared to the sample when protests are excluded. Excluding protests results in higher individual WTP estimates across all empirical estimation methods. Using the Kriström-adjusted choke price of $1,488.41, the Kriström, BART, and Bayesian probit model estimates individual WTP of $576.86, $580.86, and $575.55 respectively.

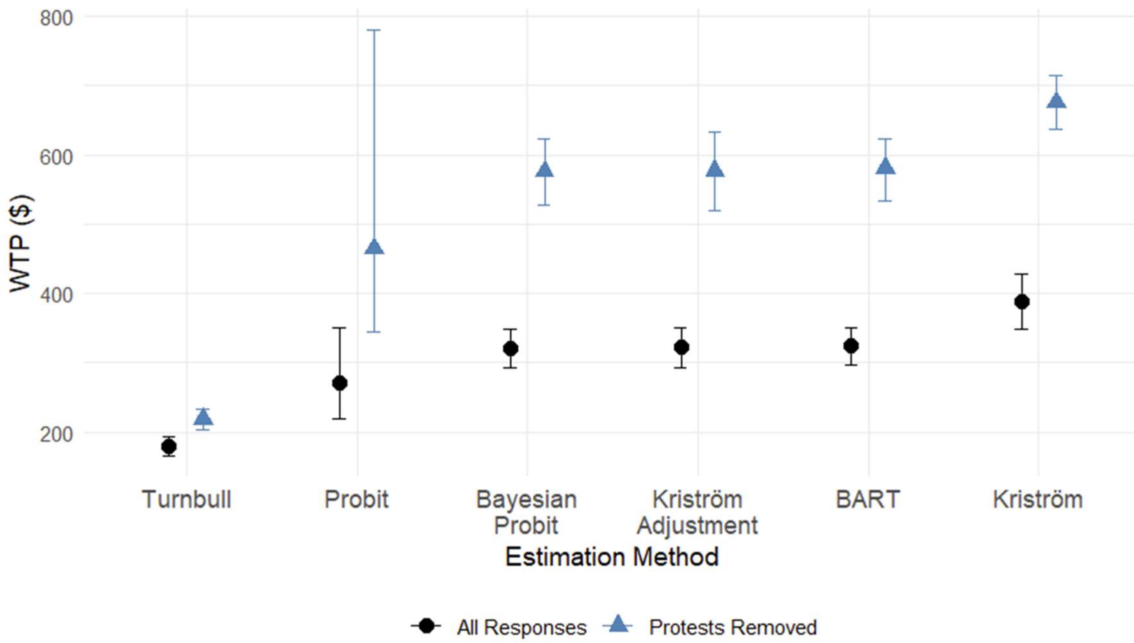

Figure 25: Sensitivity Analysis of WTP Estimates (Protests Excluded)

APPENDIX E: STATISTICAL SIGNIFICANCE TESTS

Table 9: Kruskal Wallis Rank Sum Test

Kruskal Wallis Rank Sum Test		
Variables	Kruskal Wallis Chi-Squared	p-value
Crowding Experience by *Policy Opinion*	0.801	0.938
Policy Opinion by *Crowding Experience*	27.674	<0.001
Crowding Experience by *Future Visitation*	28.7	<0.001
Future Visitation by *Crowding Experience*	65.501	<0.001

Table 9 presents results from a Kruskal Wallis Rank Sum Test on three variables from the data. *Crowding Experience* is determined by how respondents answered the question “How have the number of visitors contributed to your experience of Brooks Camp?” This question had a Likert scale that respondents could use to answer, which ranged from “Contributed Negatively (1)” to “Contributed Positively (5)”. For the statistical test, responses were coded ordinally from 1 to 5. *Policy Opinion* is an ordinal variable measured by the question “Would you support policies aimed at reducing crowding at Brooks Camp even if it meant it would be more difficult for you to visit the park on a specific day?” The respondents were presented with a Likert scale which included the responses “Strongly Oppose” (coded as 1), “Moderately Oppose” (coded as 2), “Unsure” (coded as 3), “Moderately Support” (coded as 4), and “Strongly Support” (coded as 5). Lastly, *Future Visitation* is also an ordinal variable based on responses to the statement “If crowding continued to increase, I would be less likely to visit Brooks Camp in the future.” Response options include: “Strongly Disagree” (coded as 1), “Somewhat Disagree” (coded as 2), “Neither Agree nor Disagree” (coded as 3), “Somewhat Agree” (coded as 4), and “Strongly Agree” (coded as 5).

The first two rows of Table 9 show that respondents' opinions on policies which reduce crowding (*Policy Opinion*) vary based on their experience with crowding (*Crowding Experience*). However, respondents' experience with crowding does not vary based on their opinions on policies which limit crowding. The final two rows of Table 9 indicate that respondents' likelihood of visiting in the future if crowding continues (*Future Visitation*) varies based on their experience with crowding, and respondents' experience with crowding varies based on their likelihood to visit again if crowding continues.