Managing Natural Capital for

Nature-Based Recreation in the Anthropocene

by

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ABSTRACT

Nature-based recreation is a popular way for people to interact with the environment that also confers numerous economic and health benefits. It is important that the social-ecological systems (SES) that host nature-based recreation be managed effectively, both to preserve the benefits of this important human-environment interaction, and to avoid the potential negative outcomes of recreational commons. The SES that host nature-based recreation are characterized by complex and dynamic feedbacks that complicate their management. Managing these systems is made more complex by the suite of external, multi-scalar, and anthropogenic forces (e.g., climate change, trans-boundary pollution) that plague them with increasing frequency. This dissertation investigates the importance of accounting for this full range of system feedbacks when managing for nature-based recreation.

I begin with a broad discussion of the types of dilemmas faced by managers of nature-based recreation. I create a systems based typology of management dilemmas that apply across different recreation modalities and system contexts, and which are characterized as feedbacks within the broader recreational system. My findings in this chapter have important implications for understanding and anticipating how different exogenous and endogenous shocks (including management interventions, themselves) may work through or change the processes in SES that host nature-based recreation.

In the following two chapters, I narrow my focus to examine case studies of specific dilemma archetypes and proposed management interventions. First, I perform an *ex ante* analysis of a prospective policy response to a regulatory spiral of excess recreational fishing effort and abridged fishing seasons in the U.S. Gulf of Mexico. I estimate behavioral models of fishers' responses to a prospective incentive-based intervention, and find evidence that such a policy could improve multiple fishery

outcomes. Second, I perform an *ex post* program evaluation of an invasive species bounty program. My results suggest that the program under-performed because it failed to overcome countervailing incentives.

Together, my case study analyses reveal the value of modeling for designing policy for these complex SES and show the importance of accounting for the full set of system feedbacks (including the incentives that drive recreator behaviors and the impacts of those behaviors) when managing nature-based recreation.

To Jacob and Hugo.

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Chapter 1

INTRODUCTION

Nature-based recreation is an important and popular use of natural capital that yields myriad benefits. In the United States, an estimated 164.2 million (54%) of people aged 6 and older engaged in outdoor recreation in 2021 (Outdoor Foundation, 2022). Furthermore, the non-market valuation literature reveals significant demand for high-quality nature-based recreation opportunities. Shrestha et al. (2007) find that the average visitor would be willing to pay over $70 for a visit-day of nature-based recreation in Florida's Apalachicola River region, while Sinclair et al. (2022) estimate that people are willing to pay anywhere from €6.33 to €87.16 (mean=€32.82) for recreation trips to different protected areas in Italy.[1]

Nature-based recreation generates instrumental benefits for its participants, including improved mental and physical health outcomes. Outdoor recreation has been used to treat PTSD (Wheeler et al., 2020), can help moderate ADHD symptoms in children (Kuo & Faber Taylor, 2004), and has been associated with improved mental health outcomes during the COVID-19 pandemic (Jackson et al., 2021). Furthermore, access to outdoor recreation opportunities is correlated with decreased incidence of overweight and obesity (Rosenberger et al., 2009), and increased county-level spending on parks and recreation may lead to reduced mortality (Mueller et al., 2019).

[1]The average euro-to-dollar exchange rate in 2022 was 0.951, which means willingness-to-pay ranged from $6.66 to $91.65 per-trip, and averaged $34.51 per-trip.

Table 1

Types of nature-based recreation considered in this dissertation.

Recreation Category	**Recreation Mode**
Trail Activities	Mountain biking Off-roading Equestrian Hiking
Backcountry Activities	Backpacking Camping Visit a wilderness or primitive area Foraging Rock climbing or canyoneering
Viewing & Photographing	Viewing or photographing flora or fauna
Hunting	Big and small game Waterfowl
Fishing	Freshwater Saltwater Ice fishing
Swimming	Swimming in lake/river/ocean Snorkeling Scuba diving Visit a beach or waterside
Boating	Sailing Canoeing Kayaking Rowing Motor-boating Water skiing Jet skiing Floating, rafting Sailboarding/windsurfing Surfing
Snow activities	Downhill skiing Cross-country skiing Snow-shoeing Snowmobiling

Additionally, nature-based recreation may serve as an important means of social cohesion, or as an integral part of individual or cultural identities. These "relational values," while less tangible or measurable than instrumental values, are no less important to acknowledge in discussions of managing nature-based recreation (Chan et al., 2016).

This dissertation borrows its definition of "nature-based recreation" from Cordell (2008), who describes it as, "outdoor activities in natural settings or otherwise involving in some direct way elements of nature—terrain, plants, wildlife, water bodies." The activities covered in this dissertation are sourced from a US Department of Agriculture (USDA) Forest Service technical report that adopts this same definition of "nature-based recreation" (Cordell, 2012). As this dissertation aims to shed light on emergent challenges of managing nature-based recreation during an era of unprecedented human impacts at multiple and often interacting scales (i.e., the Anthropocene), I limit my focus to modes of recreation: 1) that are under the jurisdiction of federal, state, or local natural resource managers, and 2) whose execution requires meaningful depletion of the natural capital on which they rely or which generate congestion spillovers (i.e., involve some social dilemma). Put simply, the natural capital or the quality of service flows provided by the natural capital on which a recreational activity depends must be rival. According to my two inclusion criteria, "nature-based recreation" in this dissertation includes activities like mountain biking and fishing but does not include trips to the zoo or family picnics at the park. See Table 1 for a complete list of the recreation modalities considered in this dissertation.

Nature-based recreation is usually one of myriad competing uses for the natural capital on which it depends. For example, a single forested acre could provide opportunities for high-quality recreation (e.g., birding, hunting, or hiking), contain lumber for private or commercial harvest, and generate ecosystem or biodiversity services. Some of these biodiversity services, too, feed back to recreation (e.g., the quality of a hunting experience and the amount of game encountered directly depend upon biodiversity services). These often competing uses of natural capital mean that the resource managers in charge of these systems must juggle competing biological, economic, and social objectives when designing policy.

Much of nature-based recreation takes place on public land which is managed and made available for different types of nature-based recreation by federal, state, or local resource managers.[2] Accordingly, nature-based recreation tends to occur on land or in water that is shared amongst a range of users, including other recreators, commercial interests, etc. In other words, recreation occurs in a commons, where individuals are not excluded from accessing recreational resources except perhaps through nominal fees (i.e., the commons is non-excludable), and the deer bagged by one hunter is not available for future harvest (i.e., the shared resources are rival). Olson (1965) suggests that rational, self-interested individuals who cannot be excluded from using a resource and whose individual actions are not visible to other users have no individual incentive to contribute to that resource's provision, and may instead face strong incentives to free-ride, leading to sub-optimal outcomes for the group at large in what is commonly referred to as the "commons dilemma."

One popular suggestion for overcoming the commons dilemma is to privatize the commons, such that the owner-user might appropriate rents from the conservation of that resource. However, T. Anderson and Hill (1983) argue that privatization was over-prescribed, and that the benefits of so doing may not always justify the costs.

[2] More generally, the public lands and waters that host nature-based recreation can be thought of as a type of shared public infrastructure (Anderies et al., 2004).

Another way of overcoming the commons dilemma is to introduce a lesser degree of excludability than does privatization by turning the shared infrastructure into a toll or club good.[3] Setting limits to who and how many people can access that infrastructure may limit rivalry for certain types of recreation. For example, reducing congestion on hiking trails may reduce rivalry for those hiking it. However, rivalry is inherent in certain extractive types of recreation (e.g., hunting and fishing), so introducing excludability cannot reduce rivalry for those recreation modalities.

Finally, some commons, rather than requiring outside rules, regulations, and enforcement to endure, may be governable in the long-term via collective action. Institutional scholars have found numerous examples of long-enduring, non-privatized commons systems. These scholars have shown that certain commons, and especially those that exhibit the *design principles illustrated by long-enduring institutions* (Ostrom, 1990), can be governed via collective action rather than privatization or top-down governance in the long-term.[4]

In spite of mounting evidence from institutional scholars, Dietz et al. (2003) assert that commons are becoming increasingly ungovernable via local collective action institutions. Large-scale impacts like climate change and trans-boundary pollution are especially prevalent in these systems as we progress through the Anthropocene, and these large-scale forces interact with and influence smaller-scale, local impacts as well. Managers of natural capital for nature-based recreation in the Anthropocene face a range of unique management challenges at multiple, often interacting scales.

[3]For example, recreational fishing clubs in Europe are a relatively common approach to promoting conservation by partially overcoming the incentives that drive the race to fish (Arlinghaus, 2006).

[4]The eight design principles from Ostrom (1990) are: 1) Clearly defined boundaries; 2) congruence between appropriation and provision rules and local conditions; 3) collective-choice arrangements; 4) monitoring; 5) graduated sanctions; 6) conflict-resolution mechanisms; 7) minimal recognition of rights to organize; and 8) nested enterprises, for commons that are part of larger systems.

For instance, recreational fisheries managers may stock fish or impose harvest limits on anglers based on the biological signals that they get from the fish stock. Their management actions may be helped or hindered by macro-scale preferences or norms that drive recreator behaviors, or by slow shifts in climate or rainfall patterns that drive population dynamics and create favorable habitat for invasive species. Failing to manage for the full range of dilemmas impacting a given recreational system may lead to the use of management measures that are unproductive, counterproductive or not cost-effective. Therefore, Dietz et al. (2003) stress that rules for governing commons cannot only manage for local conditions at a single point in time, but must evolve as climate change, economic markets, and other large-scale forcers in-turn change local system conditions. In other words, nature-based recreation occurs within complex adaptive social-ecological systems (SES) characterized by uncertainty and multi-scalar interactions, and should be managed as such (Blahna, Valenzuela, et al., 2020; Morse, 2020).

This dissertation showcases the importance of accounting for the full range of system processes when governing complex SES for nature-based recreation. I begin my investigation with a broad generalization of the social dilemmas facing managers across system and recreation types. Then, I narrow my focus to investigate two cases that explore different dilemmas and potential incentive-based management interventions for addressing them. These cases, while both in the realm of recreational fisheries, address different policy challenges and interventions. Furthermore, these cases feature different methodological approaches. In one of the cases, I perform a forward-looking analysis to show the power of modeling for anticipating behavioral responses to certain types of policy levers. For the other, I use a backward-looking approach to unpack behavioral responses to a policy after the fact.

In Chapter 2, I code cases of management dilemmas in nature-based recreation using the Complex Infrastructure Systems Framework and perform an archetypal analysis of those cases. I create the first—to my knowledge—descriptive, systems based typology of management dilemmas faced by recreation managers in the Anthropocene. This typology identifies eight separate dilemma archetypes, half of which emerge from recreation and the other half of which emerge from management interventions. These archetypes identify dilemmas according to their underlying feedbacks within a broader SES. By comparing cases within and between archetypes, then, I am able to identify themes regarding the interplay of system characteristics and dilemma emergence, as well as which system attributes are best-suited to different intervention approaches.

Chapter 3 features a case study with a dilemma that I define in Chapter 2 as "Leave no Trace." Fishers in the U.S. Gulf of Mexico extract red snapper faster than the stock can recover, which degrades the shared infrastructure (Gulf of Mexico red snapper) upon which the recreational headboat sector relies. In this chapter, I present a tool or method for performing *ex ante* analysis of policy counterfactuals in recreational settings, and investigate the potential for a particular incentive-based intervention to address this "Leave no Trace" management dilemma. I find evidence that uncoupling the price of access and intensive use of recreational resources can improve efficiency, mitigate externalities, and generate supplemental management revenues.

The dilemma featured in Chapter 4 is one that I term "Can't Get There from Here." The National Park Service (NPS) believes that recreational fishers at the Lees Ferry trout fishery should be accessing and extracting invasive brown trout from the fishery (and thus helping to control the population of those fish), but these fishers rarely catch and even more rarely retain brown trout within this fishery. The NPS implemented a harvest incentive or bounty on these invasive brown trout in an attempt to mobilize recreational fishers to harvest brown trout in this fishery. In this chapter, I perform an *ex post* program evaluation of that incentive-based intervention. I find that the program failed to increase brown trout harvest at Lees Ferry for several reasons. First, it did not increase total fishing trips to Lees Ferry. Second, it appears to have reduced the average number of brown trout caught per fishing trip, likely by inducing a compositional shift within the user-base. Specifically, I find evidence that more experienced Lees Ferry fishers may have avoided the fishery in response to potential crowding induced by the incentive program, while any new fishers the program may have brought in lacked the fishery-specific knowledge needed to effectively catch brown trout. The final reason for the program's under-performance is that it did not induce fishers to retain a larger share of the brown trout that they did catch.

Finally, in my concluding chapter, I synthesize my findings, reflect on their policy relevance and possible application to additional recreational systems, and suggest future avenues for research.

Chapter 2

ESTABLISHING A TYPOLOGY OF DILEMMAS FACED BY RECREATION MANAGERS

2.1 Introduction

Participation in nature-based recreation in the U.S. has been on the rise for more than a decade. In 2021, 54% of Americans aged six and up engaged in at least one outdoor recreation activity, up from 48.6% in 2010 (Outdoor Foundation, 2011, 2022). This increase in participation, paired with the rise in popularity of more destructive recreational mediums (e.g., off-highway vehicles) and the declining popularity of certain traditional forms of recreation (e.g., hunting) means managers of recreational systems face mounting challenges and uncertainty in meeting their management objectives (Collins & Brown, 2007; Cordell et al., 2005). Failure to manage for recreation can have serious consequences. In recent years, inadequately managed recreation has been linked to declines in imperiled species, the spread of invasive plants, damage to soil and vegetation, wildlife disturbance, and violations of American Indian cultural sites (Collins & Brown, 2007; Wilcove et al., 2000).

Nature-based recreation systems and the challenges their managers face are inherently social and ecological and occur at multiple, interacting scales. Consequently, a recent and growing body of literature seeks to move away from the biological and social science silos that have traditionally defined the management of outdoor recreation literature, and to instead understand nature-based recreation as part of a complex and adaptive social-ecological system (SES) (Blahna, Kline, et al., 2020; Blahna, Valenzuela, et al., 2020; Fischer, 2018; Giles, 2021; McCool & Kline, 2020; Morse, 2020). In a USDA report on the future of outdoor recreation research, Blahna, Valenzuela, et al. (2020) call for a new research agenda that focuses on, among other things, framing outdoor recreation as part of an SES in accordance with what they see as a paradigm shift from the "Active Resource Use and Management Era" (1960s-1990s) to the "Emerging Era of People and Land Interactions" (2000s-present). Furthermore, McCool and Kline (2020) argue that future research into outdoor recreation management must adopt a systems based approach that accounts for the increasing complexity of managing natural capital for recreation. Morse (2020) responds to this call by forwarding one potential way of linking and organizing existing models from multiple disciplines to represent recreation management as an SES.

In this chapter, I contribute to this budding research agenda by creating the first (to my knowledge) systems based typology of management dilemmas commonly faced by managers of nature-based recreation. This typology identifies multiple archetypes of social dilemmas faced by managers of nature-based recreation and defines those dilemmas according to the feedback structures that underlie them. In other words, I represent management dilemmas as an integral part of the complex SES that host nature-based recreation, which allows me to generate knowledge about the contexts under which certain dilemmas emerge and how management interventions targeted at those dilemmas may impact system processes and outcomes. I identify four primary dilemma archetypes that are defined by the nature of recreator-environment interactions (i.e., the recreation process), plus two categories of secondary dilemma archetypes that emerge from management interventions targeted at the primary dilemmas. Furthermore, I investigate how the interplay of different exogenous shocks, endogenous processes, and system characteristics tend to contribute to the emergence of these dilemmas. These broad archetypes and the themes I identify regarding their emergence should prove useful to recreation managers who want to model their own systems to better understand the types of anthropogenic shocks they may face, the dilemmas that may arise, and the likely outcomes (intended or otherwise) of prospective management interventions.[5]

I use the Complex Infrastructure Systems Framework (CISF) (Anderies et al., 2016) as an analytical coding framework in my archetypal analysis. Specifically, I use the CISF to code case studies of recreation management, then perform a systematic comparative analysis of those coded cases to build my archetypes. Understanding the subtleties of how local context (i.e., institutions, norms, attributes of the recreators and the environment, etc.) drive outcomes within an SES requires studying, documenting, and comparing many cases. This type of large-N, systems based comparative analysis has been used to investigate sustainability or management challenges across a range of system types, including irrigation districts (e.g., Janssen and Anderies, 2013), forests (e.g., Poteete and Ostrom, 2004; Wollenberg et al., 2007), and marine fisheries (e.g., Spijkers et al., 2018). However, this chapter is the first such comparative analysis in the realm of nature-based recreation.

In the next section, I discuss the merits of the CISF as an analytical framework for an archetypal analysis of nature-based recreation governance, then operationalize the framework to this context. Then, in section 2.3, I describe my processes for: compiling publications about managing nature-based recreation; identifying a subset of those publications that contain case studies for coding with the CISF; selecting, coding, and analyzing cases; and identifying management dilemmas. I describe four primary

[5]Anthropogenic climate change causes environmental shocks (e.g., storms, droughts, etc.) to occur at higher frequencies and intensities. Therefore, I consider all human and environment shocks to be fundamentally anthropogenic for the purposes of this chapter.

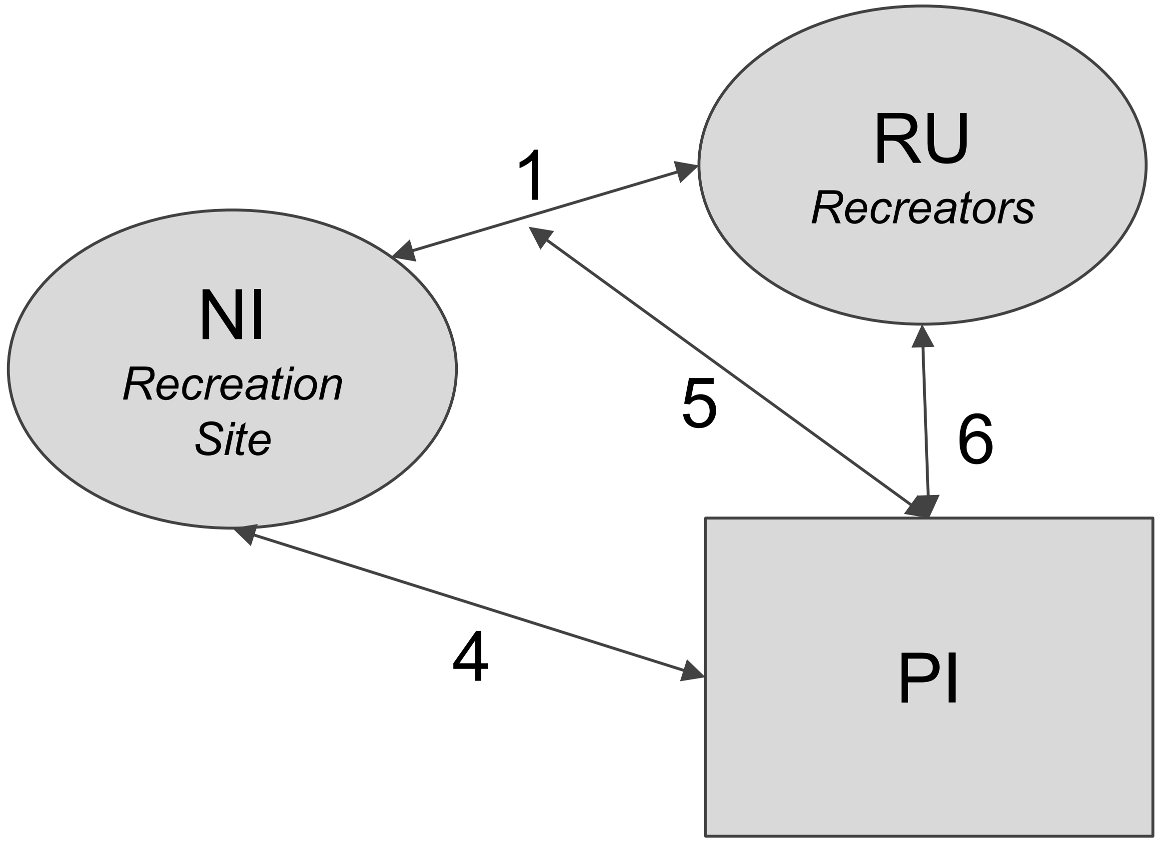

Figure 1. The CIS Framework Operationalized for Nature-Based Recreation. Adapted from Anderies et al. (2016).

and four secondary dilemmas plus themes surrounding their emergence and effective management in the Results and Discussion sections (sections 2.4 and 2.5.)

2.2 Operationalizing the CIS Framework for Nature-Based Recreation

The CISF builds upon the Robustness of Social Ecological Systems Framework (SESF) (Anderies et al., 2004; Ostrom, 2009) by introducing a unit-of-analysis mapping approach that emphasizes system dynamics. The CISF's focus on dynamics makes it an ideal analytical framework for identifying commonalities in system processes and outcomes between seemingly disparate cases of natural resource governance.

Accordingly, sustainability scholars have recently employed both the CISF and its predecessor (SESF) as analytical frameworks to underpin archetype analyses in the realms of sustainable development (Rocha et al., 2020), climate change adaptation in water governance (Gotgelf et al., 2020), rural renewal (Wang et al., 2019), governance of village pastures (Neudert et al., 2019), and the emergence of natural resource governance more generally (Aggarwal & Anderies, 2023). This chapter is the first time the CISF has been used to investigate governance across multiple modes of nature-based recreation.

Figure 1 is a visual representation of the CISF operationalized for systems that host nature-based recreation. Broadly, the CISF maps the feedbacks or processes (the numbered arrows) underlying the shared governance of the natural environment (i.e., natural infrastructure; NI). Fishers, hikers, and other resource users (RU) access the NI through link 1 to engage in nature-based recreation. The public infrastructure (PI) that directly or indirectly modifies this RU-NI process includes rules, laws, and monitoring and enforcement capacity (soft human-made infrastructure, SHMI); built features like boat ramps, trails, etc. (hard human-made infrastructure, HHMI); norms that RUs build, reinforce, or undermine and that guide their recreation behaviors in turn (social infrastructure, SI); and knowledge that RUs have about the system (human infrastructure, HI). These four elements of PI can directly influence NI through link 4, RU through link 6, and the nature of the RU-NI feedback through link 5. Examples of link 4 interventions include: stocking or culling a species, performining habitat restoration, etc. Recreation access fees, information campaigns, and fines or other modes of enforcing rules are link 6 interventions. Finally, common link 5 interventions include magazine capacity limits for hunting rifles, bait restrictions in fisheries, and prohibitions surrounding motorized trail access.

The CISF traditionally considers a fourth actor—public infrastructure provider (PIP)—too. In recreation settings, the PIP sets mandates and allocates funding for resource managers. Both of these roles are fixed within the relevant time scale of individual management case studies; laws or rules and funding availability do not often adjust quickly for managers of public land and water. For this reason, I treat the PIP node as exogenous in this chapter.

The CISF characterizes the links between RU, NI, and PI using verbs to best capture information flows or how the three elements modify or act upon one another. In a system that hosts nature-based recreation, the RU typically *accesses* (i.e., *hikes along*, *boats through*, etc.) or *extracts from* (i.e., *fishes*, *hunts*, *forages*, etc.) the NI through link 1. In return, the NI *provides utility (U)* and/or *biomass* to the RU.

While not explicitly depicted in Figure 1, any of the three system elements may be subject to exogenous shocks that—depending on the robustness of the governance feedbacks within the system—may or may not push the system toward a new steady state equilibrium. When a system flips in this way, it may cause or reveal a new management challenge.[6]

The same management challenge may emerge in two systems but for very different reasons. System A may experience a decline in biomass due to repeated recreational extractive effort, while System B sees a similar decline in response to an exogenous climate shock. While the challenge or symptom looks the same, the underlying processes and, therefore, potential effective management interventions are likely very different. The CISF provides a clear and effective template for re-defining challenges according to their underlying feedback structures (i.e., as "dilemmas").

[6]In this chapter, a "management challenge" is a problem within the system as diagnosed by the system manager. Therefore, challenges are not defined as processes or feedbacks but are instead a symptom of "failure" according to the manager's mandates.

2.3 Methods

2.3.1 Identifying Cases

In May 2022, I used the Scopus Database API Interface to curate a list of publications that focus on managing sites for nature-based recreation. In a systematic overview of bibliographic databases, Wilder and Walters (2021) find that the citation giants Web of Science and Scopus specialize in academic journal articles, and therefore have poor coverage of books, conference proceedings, and non-academic management reports. I therefore considered supplementing my Scopus results with Google Scholar or with technical reports from individual resource management agencies, but ultimately decided that using only Scopus to identify cases was more appropriate for this initial archetypal analysis. Google Scholar's search algorithm for identifying "academic-like" documents is a black box, so I have no way of identifying biases in its search results. Sourcing reports directly from management agencies would similarly bias my case selection for several reasons. First, querying all resource managers globally is infeasible, which means I would over-sample those with which I am most familiar. Second, certain agencies may be more or less willing to make their documents available to me, which would exacerbate those regional biases. Finally, natural resource managers are more often natural scientists than social scientists, which could bias the types of challenges and dilemmas I identify.

I performed title-abstract-keyword searches using a list of queries with the structure (recreation mode) AND (recreation management).[7,8] Table 17 lists all the modes of recreation I queried and their affiliated search phrases. The complete list of recreation modalities I queried includes those activities listed in a US Department of Agriculture Forest Service (USFS) technical report on participation trends in nature-based recreation (Cordell, 2012) that: 1) are under the jurisdiction of federal, state, or local resource managers, and 2) whose execution requires meaningful depletion of the natural capital on which it relies or involves some social dilemma (e.g., congestion).[9]

Finally, I merged the list of publications from all API calls and removed any duplicates ($N = 4645$.) Then, I went through the titles, abstracts, and—as necessary—body text of each unique document to determine which were relevant (i.e., focuses on managing nature-based recreation, broadly) and which should be dropped from my analysis. I used the following rules to identify 527 relevant publications:

1. Publications must focus on managing recreation on public land or waterways.
    - *Includes:* Hiking in public forests, downhill skiing that is not constrained to lodge or resort-owned land, etc.

[7] The full search phrase for "recreation management" was "(recreation OR recreate) AND (management OR manage OR managing OR planning)."

[8] I also ran a search where I replaced recreation mode in my search query with, "(outdoor OR (nature AND based) OR nature-based)" to find articles for which mode of recreation is not specified in its title, abstract, or keywords.

[9] As an example, activities like cross-country skiing or hiking tend to occur on public land, and are therefore managed by federal, state, or local resource managers. Furthermore, these activities are subject to congestion dilemmas. Conversely, organized team sports (e.g., soccer matches) and hunting at a private club are not managed by federal, state, or local entities, and their private, organized nature usually precludes social dilemmas.

- *Excludes:* Private hunting ranches, viewing opportunities at private resorts, etc.

2. Exclude valuation studies unless their purpose is to inform a management decision.
   - *Includes:* Studies that quantify benefits of or behavioral responses to a management change.
   - *Excludes:* Studies that make no mention of management or whose only mention of management is to stress its general importance for improving or maintaining the non-market value of one or more recreation sites.
3. Include publications that develop decision support tools for recreation managers.
4. Exclude studies that primarily assess potential new recreation sites without explicit consideration of day-to-day management.
5. Exclude recreation modalities that depend primarily on interaction with hard human-made infrastructure rather than natural infrastructure.
   - *Includes:* Peri-urban forests and other sites where people primarily get utility from interacting with or observing natural infrastructure.
   - *Excludes:* Built environments like boardwalks or city parks where people primarily get utility from interacting with hard human made infrastructure (e.g., playground equipment.)

After identifying relevant publications, I labeled each according to whether or not it contained a potential case study. As a rule, articles with case studies focus on one or more management challenges as identified by the system managers or case authors within a well-defined study site (e.g., a national park, a lake, a trail system). Experiments, pure simulations, and other approaches that divorce the management challenge from system context do not provide insight into the relationship between system context and management processes and outcomes, and so are not suitable cases for this chapter. I also exclude meta-reviews or analyses, because the amount of detail provided on individual cases within those reviews is insufficient to code. Finally, to limit my focus to recent emergent dilemmas, I consider only cases from documents published since 2013. Using this process, I identified 143 potential case studies.

For each potential case, I also listed the management challenges (e.g., soil erosion, recreators getting harmed or killed, etc.) identified by the system's managers or by the case authors. Then, I aggregated those symptoms into broader classes of management challenges. This aggregation process was iterative, and my objective was to create groupings that were coarse enough to apply across recreation types but narrow enough to preserve the spirit of the underlying symptoms. I collapsed 27 symptoms into six management challenges. Table 2 describes these challenges, the symptoms they represent, the recreation types for which they were identified, and the number of potential cases I identified that focus on each challenge.

Finally, I selected a sample of cases for coding from the 143 potential case studies using the following criteria:

1. For each management challenge, choose at least one case per recreation mode to ensure good coverage.
2. When possible, select cases that address more than one management challenge. This approach lets me investigate how different dilemmas tend to co-occur, and how they exacerbate or mediate each other.
3. If two or more cases shared management dilemmas and recreation types, select the case with the most detail on the RU, NI, and PI.

Table 2

Set of Management Challenges Identified by System Managers and Case Authors.

Management challenge	**Description & symptoms**	**Recreation modes**	**Case count**
Recreator harm	Recreators (resource users) are potentially physically harmed during recreation. This risk of harm may stem from zoonotic disease transmission, wildlife encounters, accidents, etc.	Trail Activities, Backpacking & Camping	6
Conflict	A spectrum of situations where the presence of other humans degrades the recreational experience. Includes congestion, physical altercations, verbal and non-verbal censure, etc.	Trail Activities, Backpacking & Camping, Viewing & Photographing, Hunting, Fishing, Swimming, Boating, Snow Activities	23
Equitable access	One or more groups of people (delineated by race, ethnicity, gender, age, etc.) have limited or no access to a recreation site.	Trail Activities, Backpacking & Camping, Swimming	5
Extractive degradation	Recreators (resource users) degrade natural infrastructure by extracting resources from the site in the course of recreating.	Trail Activities, Backpacking & Camping, Hunting, Fishing, Swimming, Boating	8
Non-extractive degradation	Recreators (resource users) degrade natural infrastructure through non-extractive site use (e.g., eroding trails, spreading invasive species, etc.)	Trail Activities, Backpacking & Camping, Hunting, Fishing, Swimming, Boating, Snow Activities	51
Wildlife disturbance	Recreators (resource users) modify the behaviors and, therefore, diminish the fitness of one or more species through proximity.	Trail Activities, Backpacking & Camping, Hunting, Fishing, Swimming, Boating, Snow Activities	60

Table 3 lists the final 18 cases I selected and their focal recreation types by management challenge.

2.3.2 Coding and Analyzing Case Studies

I followed a consistent procedure to code each case study. First, I listed the attributes of the RUs, NI, and PI. Information on RUs and NI from the time of the case study (as opposed to the present) would be difficult for me to collect and verify, which is why I coded only cases with sufficient detail regarding those system elements. However, historical PI (e.g., rules, laws, enforcement agency, etc.) are more often recorded and archived by reputable sources, so I collected supplemental information on PI on an as-needed basis.[10] My next task was to note any undesirable outcomes for the RU or NI according to the system's managers or the case authors.[11] Next, I identified the feedback(s) within and between RU, NI, and PI that described the management dilemma(s) faced by that system. Finally, I recorded potential management interventions that were suggested by the case authors or implemented by the system's managers. I also brainstormed additional interventions using my knowledge of the case's context and of other recreation systems.

[10] It was relatively common, especially in documents written by natural scientists, for the cases to include minimal details about the PI. When I could find a mission statement or stated objectives on the managing agency's official website or in a law, I used those sources to supplement my labeling of the PI node.

[11] Undesirable outcomes for RU range from a degraded recreational experience to death, while undesirable NI outcomes include soil erosion, the spread of invasive species, etc.

Table 3

Final Cases and their Recreation Modes by Management Challenge.

Management challenge	**Case**	**Recreation mode**
Recreator harm (4)	Pereira et al., 2021	Swimming
	Kubo and Shoji, 2016	Trail Activities, Viewing & Photographing
	*Hughes and Paveglio, 2019	Trail Activities
	Gstaettner et al., 2017	Swimming
Conflict (3)	Nguyen et al., 2016	Fishing
	*Hughes and Paveglio, 2019	Trail Activities
	*K. M. Brown, 2016	Trail Activities
Equitable access (2)	Höglhammer et al., 2019	Trail Activities
	McCreary et al., 2019	Trail Activities, Hunting, Fishing, Swimming, Boating, Snow Activities
Extractive degradation (3)	*Eagleston and Marion, 2017	Backpacking & Camping
	Chang et al., 2017	Hunting
	Weijerman et al., 2018	Fishing
Non-extractive degradation (6)	*Eagleston and Marion, 2017	Backpacking & Camping
	Martínez-Laiz et al., 2019	Boating
	*K. M. Brown, 2016	Trail Activities
	Bomanowska et al., 2014	Backpacking & Camping
	*Hogan et al., 2021	Trail Activities
	Carello et al., 2018	Snow Activities
Wildlife disturbance (3)	Burger and Niles, 2014	Swimming
	Spaul and Heath, 2016	Trail Activities
	Shawky et al., 2020	Viewing & Photographing, Swimming

Note: Starred cases feature multiple dilemmas.

2.3.3 Identifying Dilemmas

As I coded the case studies, I realized that many of the challenges facing recreation managers arose in response to management interventions targeted at some other challenge. These original challenges were not always explicitly acknowledged by case authors, but were easy to identify with context clues.[12] Therefore, I differentiated between primary and secondary feedbacks when coding these cases. To see both an example of my full coding process using the Martínez-Laiz et al. (2019) case and a table of coding outcomes for all 18 cases, refer to Appendix A.2.

2.4 Results

I identify four primary and four secondary management dilemmas (i.e., feedback loops). Primary dilemmas arise from the fundamental recreation process (i.e., the RU-NI interaction) and may emerge exogenously (i.e., in response to an anthropogenic shock from outside the system) or endogenously. Secondary dilemmas emerge from a primary dilemma or from a management response to a primary dilemma. Most cases feature multiple coincident or successive dilemmas, and understanding how those dilemmas interact could help managers anticipate how their own systems may transform or how any potential interventions may play out.

[12] For example, the case from Martínez-Laiz et al. (2019) focuses on the spread of aquatic invasive species. Marinas play a key role in transmission of these species, and—as HHMI—are clearly a man-made intervention designed to address some other challenge. As marinas exist to facilitate easy boat access, the symptom they are installed to treat is one of access.

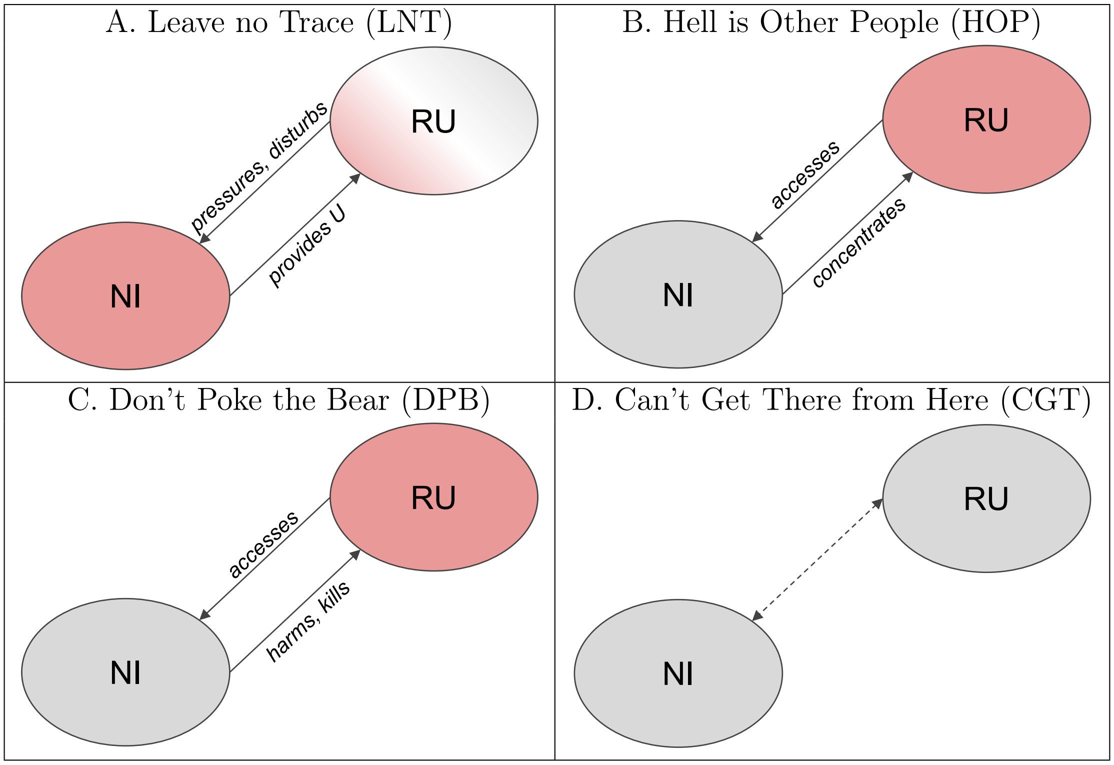

Figure 2. Depictions of the Four Primary Dilemmas. The verbs along the links indicate the modifying effects that each node has on the other. Red shading indicates the node in which the undesirable (from the perspective of the manager or case study author) outcome occurs. The partially shaded RU node in panel A indicates that RUs may or may not be made worse-off by this type of dilemma at the relevant time scale for any given case. The dashed line in panel D represents the absence of the recreational link between a particular group of RUs and some specified body of NI.

2.4.1 Primary Dilemmas

Figure 2 illustrates the four primary dilemma types. The "Leave No Trace" (LNT) dilemma type of panel A is where RUs—who get utility (U) from accessing the NI for recreation—pressure or disturb that NI, which fundamentally changes or degrades it. Panel B shows the dilemma type "Hell is Other People" (HOP), where RUs who access NI for recreation are concentrated by that NI and subsequently harmed (e.g., through a degraded recreational experience, verbal or physical abuse, etc.) through

Table 4

Overview of the Types of Cases Compared for Each Primary Dilemma Type.

Dilemma	**Cases**	**Management Challenges**	**Recreation Modes**
"Leave no Trace" (LNT)	8	Extractive degradation, Non-extractive degradation, Wildlife disturbance	Hiking, Off-roading, Camping, Rock climbing, Hunting, Fishing, Swimming, Snorkeling, Scuba diving, Visiting a beach or waterside
"Hell is Other People" (HOP)	4	Recreator harm, Conflict, Non-extractive degradation	Hiking, Mountain biking, Equestrian, Off-roading, Camping, Fishing, Visiting a beach or waterside
"Don't Poke the Bear" (DPB)	2	Recreator harm	Hiking, Visiting a beach or waterside
"Can't Get There from Here" (CGT)	4	Equitable access, Non-extractive degradation	Hiking, Viewing & photographing, Hunting, Fishing, Swimming, Boating, Cross country skiing, Snowmobiling

proximity to other RUs. "Don't Poke the Bear" (DPB) in panel C describes a case in which something inherent in the NI presents a non-trivial probability of harm or death to RUs who access it for recreation. Finally, panel D depicts "Can't Get There from Here" (CGT) in which all or certain groups of RUs have limited or no recreational access to the NI in question. This final dilemma is the most obviously subjective of the four, in that it hinges on the manager or case authors' beliefs about who *should* have access to a particular NI.

2.4.1.1 Leave no Trace

2.4.1.1.1 The Dilemma

The LNT dilemma, where extractive or non-extractive recreational activities degrade the NI on which they depend, is perhaps the most obvious of the primary dilemmas and a popular focus of conservation biologists and social scientists alike.[13] Its ubiquity may explain why this dilemma features in eight of my final cases. As a group, those eight cases focus on three management challenges and 10 unique modes of recreation. In two of these cases, LNT emerges from or is exacerbated by one or more secondary dilemmas.

I identify two important themes regarding the emergence of this dilemma. First, LNT is often exacerbated when the preferences of RUs align with NI vulnerabilities. In extractive recreation contexts, this may mean RUs preferentially harvest fish or game from a particular trophic level, simultaneously reducing biomass and transforming the surrounding ecosystem, which compromises a species' ability to recover, even if extraction ceases (Chang et al., 2017; Weijerman et al., 2018). The case described in Chang et al. (2017) illustrates a further complication where hunters get U from the experience of hunting, not from successfully bagging game. Therefore, their preferences ensure they do not exit the system or apply less extractive pressure as biomass dwindles (i.e., as NI is degraded.)[14]

[13] For example, scholars have written at length about commons dilemmas in regulated open access fisheries, where fishers degrade a fish stock through excessive harvesting (Homans & Wilen, 1997; Wilen, 2006).

[14] There is also some evidence of this trend in recreational fisheries (Kleiven et al., 2019).

In non-extractive contexts, the NI attributes that increase RU traffic (i.e., characteristics that make sites easy to access or aesthetically pleasing) may be the same characteristics that make NI vulnerable to disturbance or degradation. For example, craggy monadnocks are replete with hand and footholds, making them easier to climb than smooth cliff faces. However, vascular plants live in rock crevices, meaning undisturbed craggy routes host more biodiverse ecosystems for climbers to potentially disturb (Bomanowska et al., 2014). Similarly, Shawky et al. (2020) point out that lagoons—which are both easier to access than open ocean and aesthetically appealing—tend to host nursing female dolphins and their calves, which are especially vulnerable to disturbance from swim-with-dolphin tourists. Finally, Golden Eagles nest on cliff faces, which are high aesthetic-value sites for wildlife viewing and photography. So these eagles are most likely to be disturbed during one of the most vulnerable periods in their reproductive cycles (Spaul & Heath, 2016).

The second theme is that slow exogenous changes to RU preferences or NI resilience may cause this dilemma to emerge, either by creating a problem where none existed or by rendering a once-effective management response obsolete. For instance, in Bomanowska et al. (2014), Hogan et al. (2021), and Shawky et al. (2020), LNT emerges as increased demand for particular recreation modalities (rock climbing, ATV riding, marine tourism) in the broader population flood the study systems with enough additional RUs that their collective impact on NI becomes significant and concerning to the managers or study authors. Eagleston and Marion (2017) also notes that increased demand for camping caused Boundary Waters Canoe Area Wilderness campsites and their surrounding flora to transform. However, the larger problem facing this limited number of well-defined camp sites is macro-scale changes in camping preferences and behaviors over the past few decades. Campers today prefer smaller, more numerous, and more spaced-out tents than they did several decades ago. As a result, today's campers trample new areas of flora further outside the primary campsite ring to build "satellite camp sites" rather using only USFS-installed camp pads.

2.4.1.1.2 Management Interventions

There is a range of interventions that may address LNT, and each of these potential interventions act through one of links 4, 5, or 6. In certain circumstances, it may make sense for managers to modify NI through link 4 to correct past degradation or increase its resilience to recreational use. Weijerman et al. (2018) explain that exogenous water pollution from a nearby urban center degrades fish habitat, which makes it harder for fish stocks to recover from excess recreational fishing effort. So cleaning up that pollution or installing artificial reefs to supplement the existing habitat could, depending upon the biological context of a particular NI, help correct or mitigate this dilemma. Similarly, beach nourishment could help the sea birds and recreators described by Burger and Niles (2014) stay spatially distanced, while wildlife overpasses might help the game species from Chang et al. (2017)—whose habitat is fragmented by roads—escape or recover from hunting pressure.

Recreation managers can also act through link 4 to disincentivize especially destructive recreational activities. For example, USFS covers satellite camp sites with rocks and other hard materials to make them uncomfortable, and to encourage campers to place their tents only on official camp pads (Eagleston & Marion, 2017).

Managers may act through link 5 to moderate the impact of recreation on NI by changing how RUs access or interact with NI. In extractive settings, this type of intervention often takes the form of gear restrictions. Hawaii's Department of

Land and Natural Resources has long imposed fishing gear restrictions on recreational anglers at the reef ecosystem off Puakō, and Weijerman et al. (2018) find evidence that even more stringent restrictions on gear types could help local fish stocks (NI) recover to the benefit of multiple RU groups. Similarly, Eagleston and Marion (2017) suggest that prohibiting axes, hatches, saws, or other gear that can be used to cut trees for firewood could reduce the impact of campfires on campsite flora. However, gear restrictions may only be effective when they are enforceable. Chang et al. (2017) find that while hunters near remote villages in China are aware of and see as legitimate laws outlawing gun-ownership, they continue to use this effective, generalist weapon for hunting because enforcement is inconsistent and easy to avoid.

Gear can also increase RU impact in non-extractive settings. After the Polish Mountaineering Association installed permanent rings and other safety gear (HHMI) into select climbing routes, the number of RUs who could access those routes increased, leading to higher traffic and thus greater pressure on the vulnerable flora that grow along those routes (Bomanowska et al., 2014).

The other link 5 intervention managers can employ is to outlaw and monitor for the most impactful recreational behaviors in a system. In extractive cases where RUs are harvesting down the food web, moratoriums on harvest of particular species may help maintain trophic integrity (e.g., Chang et al., 2017; Weijerman et al., 2018). Similarly, spatial or temporal closures or activity bans that align with maximum NI vulnerability can balance demand for recreation with the need to conserve NI. For instance, Spaul and Heath (2016) suggest implementing "no stopping zones" near eagle nesting sites while nests are occupied to prevent RUs from lingering near active nests, which increases their probability of failure. Similarly, outlawing boats near the mouth of the lagoon on Samadai Reef could stop motorized RUs from trapping female dolphins and their calves in the lagoon (Shawky et al., 2020).

Finally, managers can employ information campaigns or monitor and sanction RUs for problematic and illegal behaviors via link 6. Providing tangible examples of how certain undesirable RU behaviors impact NI could induce some RUs to behave differently to moderate their own impact. This type of intervention would likely work best when the impacted NI is charismatic. Monitoring and enforcement may be required when the NI is not charismatic or when the negative outcome is less directly tied to an individual RU's actions. For instance, the plant that is negatively impacted by illegal ATV riders on Miscou Island is not charismatic, so RUs may have little motivation to give up pleasure from their recreational pursuits to protect it (Hogan et al., 2021). On the other hand, Golden Eagles and Spinner Dolphins are both charismatic species, but the impact of a single recreator on eagles is much clearer than on dolphins; one pedestrian lingering too long can cause nest abandonment and chick death, while one swimmer approaching a mother-calf dolphin pair may cause them to spend less time resting, which only appreciably impacts their fitness and survival over repeated encounters (Shawky et al., 2020; Spaul & Heath, 2016).

Monitoring and enforcement may be difficult for managers with funding constraints, when the NI is diffuse and easy to access, and when informal institutions (SI) arise to block enforcers. The government of New Brunswick has limited funds to devote to monitoring for illegal ATV use on Miscou Island, and RUs can ride all over the large, remote coastline, meaning there are no obvious access points at which to focus monitoring (Hogan et al., 2021). The forests utilized by hunters in rural China are similarly large with numerous official and unofficial access points, making them difficult to monitor for illegal hunting (Chang et al., 2017). Furthermore, informal information-sharing networks (HI) have emerged to help those hunters avoid detection when enforcers arrive at their villages. In this case, the authors suggest a shift from national to local governance of hunting may increase legal compliance and reduce pressure on the NI.

Similar to the hunting case, enforcers have long been required on dolphin viewing vessels, but social norms (SI) prevent their enforcing rules about speed limits and aggressive driving designed to trap dolphins in the lagoon (Shawky et al., 2020). In cases where RUs must utilize PI (e.g., trails, boat launches, etc.) to access NI, recreation managers could potentially use technology to circumvent enforcement-blocking norms. For instance, requiring cameras or gps trackers on boats could help an impartial third party identify reckless or illegal boating behaviors, creating a credible risk to trapping dolphins in the lagoon.

2.4.1.2 Hell is Other People

2.4.1.2.1 The Dilemma

The four cases I compare to identify and describe this dilemma feature three management challenges and seven unique modes of recreation between them. For two of these cases, HOP is the sole dilemma, while in the other two it either precedes or is amplified by a secondary dilemma. I will discuss in more detail how this primary dilemma interacts with those secondary dilemmas in section 2.4.2.

This dilemma may emerge quickly in response to some exogenous anthropogenic shock, or it may emerge and intensify slowly as a positive feedback loop that causes and is fed by repeated negative interactions between heterogeneous RUs. In the former case, managers can try to anticipate potential shocks and preemptively invest in PI that improves their triage capabilities (e.g., setting up and raising awareness for an information-sharing web page, buying cameras to monitor RU behaviors, or hiring additional enforcers, etc.) The types of sudden anthropogenic shocks that could spawn HOP in recreational systems are expected to increase in frequency as we progress through the Anthropocene. For example, beachgoers in Pará became hazards to one another only after COVID-19 increased the number of RUs at the beach while at the same time creating a new risk—namely, transmission of a dangerous zoonotic disease—to RU proximity (Pereira et al., 2021). The incidence of zoonoses is expected to increase dramatically over the next few decades, meaning recreation managers should anticipate RUs suddenly and increasingly becoming hazards to one another in the near future (Carlson et al., 2022).

This dilemma emerges slowly and purportedly as a result of RU heterogeneity in three of my final cases. The types of heterogeneity that drive emergence in these cases are of RU values, behaviors, and recreation modalities. Hughes and Paveglio (2019) note that an exogenous increase in ATV participation may partially explain the increasing ratio of newcomers to legacy RUs at the St. Anthony Sand Dunes. Newcomers' riding behaviors are more dangerous to themselves and others, so over time the slow compositional shift within RU degraded the recreational experience of legacy participants, many of whom eventually fled the system, further accelerating the dilemma. Managers should, therefore, collect data on the share of legacy versus new RUs to better anticipate the potential emergence of HOP.

The cases described by K. M. Brown (2016) and Nguyen et al. (2016) also exhibit positive feedback loops associated with RU heterogeneity, but these cases are not a story of compositional change; the heterogeneity driving the feedback is between different legacy RU groups. K. M. Brown (2016) shows that RUs of different recreation modalities may find it hard to empathize and co-exist with the other group, and that repeated negative interactions may "flip" a system by transforming the use norms (SI) of one or both groups. Similarly, Nguyen et al. (2016) discuss how RU groups with different values may have trouble empathizing with one another, and may even resort to sabotage or physical violence to settle disagreements about use and access rights.

2.4.1.2.2 Management Interventions

There are three broad types of intervention that managers may employ to address HOP. Managers may: 1) limit the number of RUs for the NI to concentrate, 2) encourage or force RUs to spatially or temporally spread out, or 3) mediate the negative impact of RUs being concentrated.

The first intervention may mean anything from disallowing all access (i.e., temporarily or permanently closing a recreation site) to limiting RU access through space and time. Complete closures, where managers set SHMI to outlaw any and all RUs through link 6, may be effective if the dilemma is caused by a sudden and (relatively) short-lived exogenous shock. For example, during the height of the COVID-19 pandemic, several municipal tourism departments in Pará, Brazil, closed their beaches to prevent viral transmission (Pereira et al., 2021). However, when the threat to RUs is persistent, managers may instead limit the number of RUs accessing, and thus being concentrated by, the NI. For example, several Pará municipalities disallowed beach access via public transportation, which means potential RUs without car access and who live too far from the shore to walk are *de facto* excluded from these systems via link 6 (Pereira et al., 2021). Other methods of access limitation could include setting and enforcing rules regarding RU capacity (link 6) or imposing or increasing access or parking fees (link 5) to dissuade excess participation. Blocking RU access is only feasible for systems with NI that funnels RUs through a limited number of well-defined and easy-to-monitor access points. Hence, the beaches with parking lot access from Pereira et al. (2021) are potential candidates for this intervention type, while the relatively unbounded St. Anthony Sand Dunes from Hughes and Paveglio (2019) are not.

The second intervention approach of facilitating RU spread may work through any of links 4, 5, or 6, but the instances for which each link may be an effective intervention point depends upon the nature of the RU and NI for a particular system. Managers may install physical partitions in the NI (link 4) to limit the ability of RUs to congregate, as was done at some beaches during the COVID-19 pandemic (Pereira et al., 2021). However, this approach depends upon the NI being sufficiently concentrated or well-defined (as is the case for beaches but not for sand dunes). Furthermore, these installations must either bind RU behaviors or RUs must be willing to abide by the suggestions implicit in those installations. For example, beach managers in Pará installed umbrellas and tables in a spaced-out fashion to discourage congregating (Pereira et al., 2021). However, these installations were not binding on RU behavior (i.e., this HHMI was moveable) and RUs were unwilling to contain their shoreline recreation to the HHMI-defined zones.

Recreation managers may also limit RU concentration by altering how RUs access NI (i.e., setting rules that act through link 5). For sites with well-defined and spatially-concentrated access points, managers may allow or encourage the use of vehicles or other technologies that facilitate spreading out (Pereira et al., 2021). Alternately, if the threat the RUs pose toward one another correlates with observable RU attributes, then managers can spatially and temporally allocate access to these attribute-delineated RU groups to keep them separated. For example, in both K. M. Brown (2016) and Nguyen et al. (2016), RUs are harmed (psychologically or physically) by proximity to other RU groups. Furthermore, the RU groups are differentiated along observable attributes that managers could potentially use to separate them via rules and regulations.[15] However, while segregating RU groups may work in theory, managers may often face exogenous mandates that prohibit this type of intervention. For instance, the Land Reform Scotland Act of 2003 makes all paths multi-use, which means managers at Cairngorms National Park cannot legally zone by recreation mode (K. M. Brown, 2016). Similarly, the fishery managers from Nguyen et al. (2016) have limited ability to separate First Nation and recreational salmon fishers thanks to a Supreme Court ruling granting First Nation fishers constitutional rights to salmon above all other user groups. This fishery case illustrates a further complication, which is that certain NI attributes may make zoning access by RU group impractical. Salmon are anadromous, so access rights to salmon and other non-stationary NI must be zoned both spatially and temporally, which is both more complicated and uncertain than a simple spatial delineation.[16]

Finally, recreation managers can use information campaigns to encourage RUs to spread themselves out spatially or temporally via link 6. This approach will be effective only if the spatial or temporal zones are easy to monitor and easy for RU to identify and if RUs are motivated to avoid close contact. So managers at Cairngorms National Park could install trail cameras and publicize live and historical counts of

[15] In K. M. Brown (2016), RU groups are delineated by recreation mode (hikers versus mountain bikers) while in Nguyen et al. (2016) groups are culturally defined (First Nation fishers versus non-indigenous recreational fishers.)

[16] Anadromous fish are those that migrate up-river from the sea to spawn.

hikers and mountain bikers on particular trail segments to help those groups avoid each other (K. M. Brown, 2016). However, the U.S. Bureau of Land Management (BLM) may find it difficult to count ATV riders at the St. Anthony Sand Dunes, and the open nature of the NI would make it difficult for RUs to employ that information to avoid busy areas (Hughes & Paveglio, 2019).

Mediating potential harm from RU concentration can either mean changing how RUs are allowed access the NI (link 5) or setting rules and sharing information via link 6 to change RUs' perceptions and behaviors more broadly. In instances where the risk of RU harm stems from reckless behaviors, recreation managers can implement speed limits, right-of-way laws, and other safety regulations to force responsible access behavior through link 5. In some cases, managers may be able to enshrine into law norms which had previously prevented or mitigated HOP. For example, the St. Anthony Sand Dunes was previously governed by a set of informal, user-cultivated norms. The influx of newcomers caused this collective action to break down, but the BLM could draw from this legacy *dunes culture* to develop use rules that are tailored to the site. Hughes and Paveglio (2019) suggest that legacy users, many of whom are locals, be included in governing the St. Anthony Sand Dunes (i.e., RU = PI) to leverage their site-specific knowledge and expertise.

In some circumstances, managers may be able to correct harmful or reckless behaviors through an information campaign (link 6) instead of resorting to formal regulations. Thanks to their multi-use trail mandates, managers at Cairngorms National Park cannot legislate right-of-way, as that would give either hikers or mountain bikers a priority use right. However, K. M. Brown (2016) points out that managers could resolve some of the uncertainty and fear experienced by hikers and mountain bikers by advertising best practices and otherwise reinforcing a common understanding of trail etiquette. Campaigns designed to change RU behaviors do not have to be limited to information on best practices; managers can also reduce fear and uncertainty surrounding inter-group encounters, build empathy and encourage cooperation by emphasizing commonalities in RU groups' recreational experiences, play up common enemies, or educate different RU groups on the origin of each others' rights (K. M. Brown, 2016; Nguyen et al., 2016). However, both laws and information campaigns may be ineffective at inducing desired behaviors if there is insufficient enforcement and if RUs are not convinced a significant risk exists. For example, beachgoers in Pará—many of whom did not believe COVID-19 was very infectious—ignored regulations requiring social distancing and the use of personal protective equipment (Pereira et al., 2021).

2.4.1.3 Don't Poke the Bear

2.4.1.3.1 The Dilemma

Two of my final cases exhibit DPB, and one of those cases also features a secondary dilemma that emerged from a management response to DPB. Both Kubo and Shoji (2016) and Gstaettner et al. (2017) identify situations where RUs get U from the activity that has the potential to harm or kill them. In the former case, non-local hikers want to observe brown bears on the Numameguri Hiking Trail in Hokkaido, Japan. The latter case examines the motivations of non-local beachgoers in Western Australia to walk on a sandbar against posted advice. In both cases, the vulnerable non-local RUs are attracted by novel, exciting, and inherently dangerous experiences, and would experience significant reductions in enjoyment if the dangerous activity were prohibited.

2.4.1.3.2 Management Interventions

One obvious solution to DPB is to impose rules (SHMI) or physical barriers (HHMI) to keep RUs away from "the bear" through link 5. Walking on the sandbar between Mersey Point and Penguin Island is illegal during inclement weather, and the managers of Daisetsuzan National Park close segments of the Numameguri Hiking Trail when a bear is spotted nearby (Gstaettner et al., 2017; Kubo & Shoji, 2016). However, banning risky behaviors significantly degrades the recreators' experiences, especially—as is the case in Western Australia—when the thrill of taking a risk contributes to the activity's appeal (Gstaettner et al., 2017). So recreation managers may consider alternate interventions that either help RUs assess and prepare for their personal risk level or that minimize the realized risk of the activity without disallowing it entirely.

When RUs routinely underestimate their own risk of harm, recreation managers can employ narrative and information campaigns via link 6 as a reality check. For example, Gstaettner et al. (2017) find that beachgoers, and especially international visitors, routinely compare themselves to other sandbar walkers who appear more vulnerable than themselves, which leads most people to underestimate their own risk of mortality. One visitor saw a child on the sandbar with their parents and assumed that they—an adult—must be a stronger swimmer than that child, even though they later admitted they were a poor swimmer. Gstaettner et al. (2017) suggest that using narratives that counter the ways in which RUs overcome cognitive dissonance (e.g., publicizing the news of a strong swimmer who drowned on the sandbar) might be an effective way to discourage high-risk individuals from participating in unsafe forms of recreation.

Information campaigns can also help RUs engage in risky but rewarding recreational activities in a safer way. In the Western Australia case, for example, the sandbar is dangerous, in part, due to its unpredictable and dynamic nature (Gstaettner et al., 2017). Therefore, providing information about when the risk is highest (in the afternoon during high tide) might help people who plan to walk the sandbar substitute to a safer time of day. Similarly, Kubo and Shoji (2016) point out that larger hiking groups are less vulnerable to brown bear attacks. Brown bears tend to congregate further from trail heads, so Kubo and Shoji (2016) suggest managers either recommend (link 6) or require (link 5) minimum group sizes for more remote trail segments.

2.4.1.4 Can't Get There from Here

2.4.1.4.1 The Dilemma

While I identify four case studies related to this dilemma, two of those cases focus on the dilemmas that emerged after access was established (i.e., after some managing body decided CGT existed and addressed it.) This goes to show that the moment someone provides PI to enable or improve access to NI, even non-extractive types of access, secondary management dilemmas often follow. In this section I engage with the two cases for which CGT is the focal emergent dilemma. I discuss the other two cases in the context of their secondary dilemmas in section 2.4.2.

For both cases in which CGT is the focal dilemma, the management challenge identified by the authors is "equitable access." Together, these cases cover a wide range of recreation modalities, all of which are listed in Table 4. Höglhammer et al. (2019) investigate the barriers that Chinese and Turkish immigrants face in accessing the Wienerwald Biosphere Reserve (WWBR) in the Austrian Alps, while McCreary et al. (2019) discuss the extent to which different sociodemographic groups are able to adapt to climate change shocks in order to access Lake Superior's North Shore for recreation.

These two cases illustrate that RU groups may face language, cultural, or fear and uncertainty barriers to accessing NI for recreation. Furthermore, these barriers may correlate with observable RU attributes, making them easier to address but also a potential source of inequity. Höglhammer et al. (2019) find that Chinese and Turkish immigrants face different cultural and language barriers to accessing the WWBR; both groups are unaware that their preferred modes of recreation are not only allowed but encouraged within the WWBR. This disconnect exists both because the immigrants' preferred modes are not much advertised by site managers, and because WWBR managers and immigrants often use different words or phrases to describe the same activities. For example, the Chinese immigrants reserve the word "hiking" for strenuous outings and prefer to "take walks in nature," which WWBR managers understand to be a form of hiking. Therefore, many Chinese immigrants are uncertain about or fearful of accessing the WWBR without a guide or gatekeeper from their own community. Barriers that correlate with languages or cultures are likely to become a more common issue in the near future, as the increased severity and frequency of epidemics and weather events caused by anthropogenic climate change create climate refugees (Beine & Parsons, 2015).

Rather than being language or culture-based, the access barriers identified by McCreary et al. (2019) lie along sociodemographic margins. Specifically, these authors find that older, lower income, and first time visitors to Lake Superior's North Shore are less able to adapt to severe weather events—whose frequency and intensity are augmented by climate change—and are therefore more likely to exit the system. The relative inability of older recreators to adapt could be especially impactful given that high-frequency participants in outdoor recreation are an aging group (Outdoor Foundation, 2022), and the over-representation of lower income individuals amongst system leavers is an obvious equity concern.

2.4.1.4.2 Management Interventions

In general, the most effective way to overcome barriers to access may be to include members of underrepresented groups in decision making (RU=PI). Höglhammer et al. (2019) suggest recreation managers provide guides or gatekeepers from different migrant communities to mitigate the fear and uncertainty that RUs from those communities experience when visiting a new site. Another way to minimize this uncertainty would be to employ members of underrepresented communities in designing and disseminating informational materials (link 6) to ensure that the types of activities advertised and the way those activities are described are accessible and salient across RU groups.

When barriers to access are related to sociodemographic factors like age and income, it is important to understand what types of adaptations those groups are willing and able to perform to continue recreating. In the case described by McCreary et al. (2019), it is possible that lower income RUs were less able to afford technology adaptations or engage in temporal substitution to avoid severe weather events. Similarly, older RUs

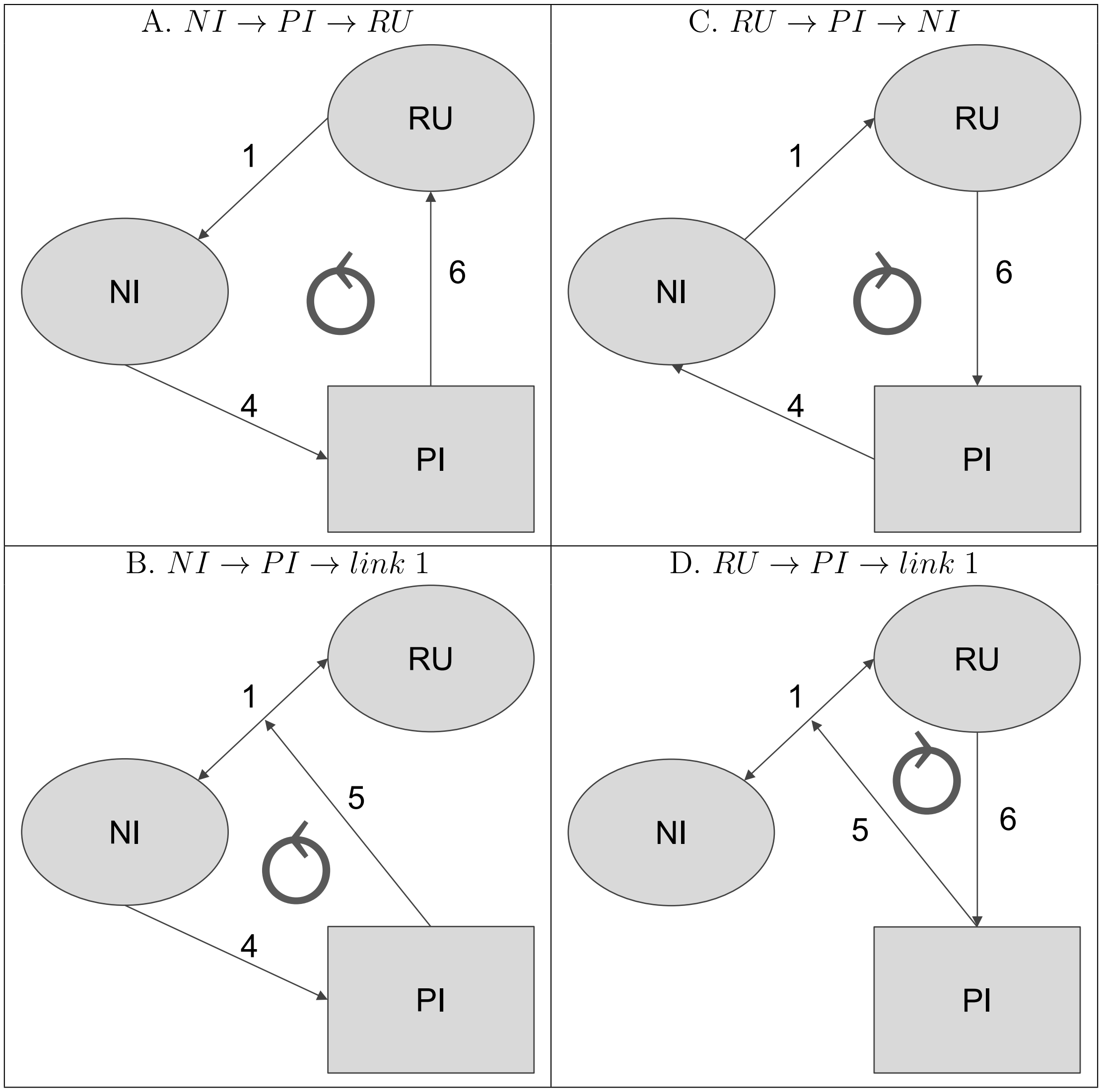

Figure 3. System Diagrams of the Four Secondary Dilemma Archetypes.

may be unwilling to adopt new technologies or less physically capable of adapting to extreme conditions. In either case, managers may want to emphasize low-cost and low-tech risk-mitigation approaches to help these vulnerable groups remain in the system.

2.4.2 Secondary Dilemmas

I identify four types of secondary, PI-involved dilemmas that tend to emerge either from management responses to one of the primary dilemmas or from a transformation of PI caused by a primary dilemma. The two archetypes in the left column of Figure 3 involve *counter-clockwise* information flows, while the flows of information or biomass depicted in the right column are *clockwise*. The counterclockwise processes involve the PI acting upon RUs (link 6) or their access behaviors (link 5) after receiving some information or biomass signal from NI (link 4). In the clockwise processes, the PI acts upon NI (link 4) or affects how RUs access NI (link 5) in response to an information signal from the RUs (link 6).

2.4.3 Counter-clockwise Dilemmas

In the cases I compared, these dilemmas usually present as a flow of information that arises from or in response to LNT. This trend makes sense, because in counter-clockwise dilemmas the PI responds to information signals from the NI. Two of my cases feature dilemma A from Figure 3 (McCreary et al., 2019; Nguyen et al., 2016), while the case described by Kubo and Shoji (2016) focuses on dilemma B. See Table 5 for a description of these four cases. In all three cases, RU heterogeneity contributes to the secondary dilemma, but the margin along which RU heterogeneity occurs is only a reasonable management target in two of those cases. Salmon is valued and extracted differently by Alaskan First Nation and recreational fishers, which means these two groups differ in their stock impacts, too (Nguyen et al., 2016). Indigenous status, then, is a relatively easy and important margin along which to differentiate

Table 5

Descriptions of Cases that Feature Counter-Clockwise Secondary Dilemmas.

Case	**Emergence**	**Secondary Dilemma**	**Outcome**
Kubo and Shoji, 2016	Managers setting rules to address DPB.	Type B. Information feedback. PI monitors and receives information on bear locations through link 4. When managers sight a bear near a trail segment, they close that segment (link 5). This asymmetrically reduces the U that local and non-local RUs get from hiking in the park by spatially restricting their access.	CGT
McCreary et al., 2019	Managers sharing information to address DPB.	Type A. Information feedback. PI monitors weather (link 4) and publicizes that information for RUs (link 6). Certain RUs no longer access NI through link 1 in response to that information.	CGT
Nguyen et al., 2016	Managers setting rules to address LNT.	Type A. PI monitors salmon stock (link 4) and based on stock health allocates different quantities of fish to the First Nation and recreational fishers according to exogenous laws or mandates (link 6). Both RU groups see allocation as unfair, so they clash.	HOP

SHMI. However, this case suggests that when RU heterogeneity is correlated with identity, an us-versus-them mentality may well exist and create what Nguyen et al. (2016) call a "blame game," which in this case is a Type A counter-clockwise dilemma. The two RU groups fish from the NI, and the PI gets information about their collective stock impact by monitoring NI. In response to signals regarding stock health, the PI imposes different harvesting rules on the recreational and First Nation fishers.

The RU groups then clash with each other in response to perceived procedural or distributional unfairness related to their different fishing rules.

Heterogeneity in RU is similarly easy to identify and target with policy in the case described by Kubo and Shoji (2016). Local and non-local hikers at Daisetsuzan National Park have different preferences for bear viewing, and are therefore unequally impacted when managers close trail segments in response to bear sightings (Kubo & Shoji, 2016).[17] So providing different information or rules for locals versus non-locals—which is a reasonable management target—could improve outcomes for both RU groups. In contrast, the relevant margin of RU heterogeneity for Lake Superior recreators is ability to adapt to anticipated weather shocks, which is loosely correlated with multiple sociodemographic characteristics (i.e., age and income) and is therefore difficult to target (McCreary et al., 2019). Specifically, when the PI publicizes weather alerts through link 6, certain RU groups are more likely to not access the NI rather than try to adapt to the anticipated weather shock. This latter case emphasizes how important RU heterogeneity can be in determining system outcomes, even when it cannot be directly targeted by managers. Conditional on knowing that older and lower income RUs were disproportionately impacted by anticipated weather shocks, the Minnesota DNR—whose mandates include providing information and technical assistance to citizens and local governments—could help different RU groups overcome barriers to adaptation by providing gear or working with repeat RUs to compile informational resources that facilitate adaptation by different RU groups (e.g., suggesting low-cost adaptations for RUs with lower household incomes.)

[17]Through monitoring efforts, the PI receives information from the NI that a bear is near a certain trail segment. In response to this signal, the PI closes access that trail segment, which is a link 5 intervention. This access restriction reduces the U that RUs can get from accessing NI, and the amount of U lost is greater for non-local RUs who value bear sightings.

2.4.4 Clockwise Dilemmas

Clockwise dilemmas start as information flows from RU to PI, so they tend to emerge from primary dilemmas that lead to RU harm (e.g., CGT and HOP). However, this general trend surrounding the emergence of clockwise dilemmas does not always hold. In the case from Hughes and Paveglio (2019), for example, a Type D secondary dilemma emerges due to an exogenous shock to RU, and in Martínez-Laiz et al. (2019), the Type C feedback circulates biomass rather than information. For a full description of how these secondary clockwise dilemmas emerge and their outcomes across five case studies, see Table 6.

As stated previously, any intervention that overcomes CGT will likely cause another dilemma, and often one whose outcome is the degradation of NI. The cases from Carello et al. (2018) and Bomanowska et al. (2014) are examples of this trend. In both cases, recreation managers modified NI to facilitate recreational access, and their management actions resulted in degraded NI. However, the way in which these interventions impacted the NI differs. Recreation managers trim willow grasses in Cucumber Gulch every autumn and subsequently compact the snow over those clipped grasses with heavy machinery to create pristine cross-country ski trails. It is this modification that degrades the NI (i.e., the pressure is through link 4), because cross-country skiers do not sufficiently pressure the landscape to cause degradation (Carello et al., 2018). So this case exhibits secondary dilemma type C. Conversely, after the Polish Mountaineering Association installed permanent accessibility rings into monadnocks within the Krakow-Czestochowa Upland, the resultant increase in climbing activity (thorough link 5) hurt the fitness of the vulnerable vascular flora on those stretches of limestone (Bomanowska et al., 2014). The mechanism for harm

Table 6

Descriptions of Cases that Feature Clockwise Secondary Dilemmas.

Case	Emergence	Secondary Dilemma	Outcome
Bomanowska et al., 2014	Installation of HHMI to address CGT.	Type D. Information feedback. In response to increased demand for rock climbing (link 6), the Polish Mountaineering Association installed HHMI to improve safety and increase access to certain routes, which facilitated increased NI access (link 5).	LNT
K. M. Brown, 2016	HOP transformed PI.	Type D. Information feedback. Mountain bikers maintain use norms (link 6) that drive their recreational behaviors (link 5). The norms flipped from responsible use to reckless use in response to alienation.	HOP amplified
Carello et al., 2018	Modification to NI to address CGT	Type B. Information feedback. In response to demand for winter sports (link 6), recreation managers clip and compact willow grasses annually to prepare cross-country ski trails (link 4).	Degraded NI
Hughes and Paveglio, 2019	Exogenous shock to RU composition.	Type D. Information feedback. ATV riders maintain use norms (link 6) that drive their recreational behaviors (link 5). The norms flipped from responsible use to reckless use when a critical mass of newcomers entered the system.	HOP
Martínez-Laiz et al., 2019	Installation of HHMI to address CGT.	Type C. Biomass feedback. Marinas (PI) collect invasive species from the surrounding sea (link 4). Marinas transmit those invaders to RUs via their stored boats (link 6), and those RUs then deliver the invaders to other parts of the sea (link 1).	LNT

in this case is the facilitation of greater RU access, and so it is a type D secondary dilemma.

The case in Martínez-Laiz et al. (2019) is another example of an intervention designed to address CGT causing NI degradation. Specifically, this case illustrates how HHMI designed to facilitate NI access can unintentionally create a channel for biomass to flow through. Leisure boaters utilize marinas to access different parts of the sea. However, the HHMI itself collects potential invaders and transmits them to boat hulls. It is important, then, to consider that HHMI may become habitat for undesirable species, creating a difficult-to-anticipate dilemma. The remedy, short of demolishing these marinas, is to break link 6 by ensuring boats aren't infected before leaving the marina. This outcome could be accomplished by updating boat cleaning recommendations, or by fining recreators who arrive at a marina with a critical mass of invaders in their hull.

Comparing the cases in K. M. Brown (2016) and Hughes and Paveglio (2019) provides clues to how HOP dilemmas may emerge and accelerate thanks to clockwise secondary dilemmas. Specifically, these cases illustrate how a feedback loop that is driven by collective action and mediates or prevents some primary dilemma might be "hidden" to managers until some force transforms system norms (PI) and thus the nature of the secondary feedback, rendering it problematic. For many years, legacy ATV riders in the St. Anthony Sand Dunes built and maintained a set of norms (SI) or a *dunes culture* (link 6) of courteous riding behaviors (link 5) that ensured all RUs, not just ATV riders, stayed safe and enjoyed their recreational experiences. However, a flood of newcomers eroded the traditional *dunes culture* (link 6) and transformed it into a set of more reckless and self-interested riding norms that endanger RUs and degrade the experiences of especially vulnerable groups (e.g., families with children) (Hughes & Paveglio, 2019).

Similarly, a transformation in use norms turned an "invisible" feedback that minimized the negative impact of mountain bikers on other RUs and on the NI of Cairngorms National Park into a visible and problematic HOP dilemma (K. M. Brown, 2016). However, whereas the transformation in Hughes and Paveglio (2019) was due to an exogenous increase in newcomers, the PI transformation in this case was due to a long history of negative sentiments between the hiking and mountain biking RU groups. Over time, mountain bikers were made to feel alien or excluded, and eventually reached what K. M. Brown (2016) call the "disengagement tipping point" where they divested themselves of their traditional, responsible use norms (link 6) and committed instead to more myopic riding behaviors (through link 5).

2.5 Discussion

My descriptive, archetypal analysis of management case studies in the realm of nature-based recreation generates several intellectual contributions and paves the way for future, more prescriptive work regarding the effective management of nature-based recreation in the Anthropocene. Broadly speaking, my results highlight how essential it is to account for the full set of feedbacks when designing policy for coupled human-environment systems. This finding echoes that of Fenichel et al. (2013), who conclude that more interdisciplinary models that explicitly incorporate behavioral responses and biological processes are needed to improve recreational fisheries management.

In this section, I identify processes that operate across very different recreation types as well as some themes surrounding when those processes break down. I describe the roles that RU heterogeneity and dilemma visibility often play in creating and amplifying management dilemmas in this space, then discuss the full portfolio of interventions available to recreation managers. In my discussion of management interventions, I pay particular attention to the interplay between system attributes and intervention feasibility and efficacy.

2.5.1 Common Processes and Where they Break Down

Regardless of recreation mode, the basic underlying feedback in nature-based recreation is that RUs access and get U from NI. Similarly, the four primary dilemma archetypes (i.e., ways in which that basic process may break down) I identify are not directly determined by the mode(s) of recreation that characterize a particular system. For example, Table 4 reveals that LNT emerges in systems that host a range of extractive (i.e., hunting and fishing) and non-extractive (i.e., hiking, camping, etc.) recreation modalities. Similarly, these dilemmas present as different management challenges according to factors like RU or NI characteristics, prevailing management mandates, etc. The manager who seeks to prevent "recreator harm" from the spread of an infectious disease and the manager whose system is marked by violent RU "conflict" face the same fundamental dilemma (HOP). There is no reason, then, that fisheries managers need only study other fisheries nor trail managers other trail systems when diagnosing and exploring potential interventions for their dilemmas. Rather, these managers could benefit from studying how others—with their unique mandates and perspectives—addresses similar fundamental break-downs in the NB-recreation process.

In the interest of helping managers diagnose and address these inter-modal dilemmas, I identify two key trends surrounding their emergence. First, RU heterogeneity is a common driver or amplifier of these dilemmas. Second, managers can address only dilemmas that are visible to them. Dilemma visibility is determined by monitoring capacity, management mandates (i.e., what defines success and for whom?), the speed at which the dilemma emerges (i.e., was it gradual enough to avoid detection?), and whether or not some similarly invisible feedback exists that mediates and obscures the dilemma but which managers could accidentally undo or that might erode over time. I discuss these two themes in more detail in the following two sections.

2.5.1.1 RU Heterogeneity

RU heterogeneity can take a variety of forms, some of which are more visible than others. For example, RU groups may use different modes of recreation, hold different values, have different levels of site-specific knowledge, come from different cultural or ethnic backgrounds, speak different languages, or be more or less adaptable in the face of anthropogenic shocks to the system. Similarly, heterogeneity between RU groups may play several different roles in creating or amplifying a management dilemma, sometimes even within the same system. Heterogeneous users may be more prone to conflict if they find it difficult to empathize with one another (e.g., the recreational and First Nation fishers from Nguyen et al. (2016)), and RUs with different values and preferences may differentially contribute to and be impacted by emergent dilemmas (e.g., legacy versus newcomer ATV riders in Hughes and Paveglio (2019).) On a related note, management interventions will likely advantage or disadvantage RU groups differently depending on how well each group's use ethics or perspectives do or do not align with those of the managers. In other words, some RU groups are more vulnerable than others, either because they are less resilient to certain system shocks and dilemmas (e.g., older and lower income recreators at Lake Superior) or because they are relatively under-served by managers (e.g., Chinese and Turkish immigrants at WWBR.)

Addressing sources of RU heterogeneity that drive or amplify dilemmas can pose a significant challenge. In some cases, it may not be possible to target management interventions at the relevant margins of heterogeneity. For example, swimming ability and knowledge of sandbar dynamics—which loosely correlate with local versus non-local status—play a significant role in determining an individual's risk level from walking on the sandbar to Penguin Island (Gstaettner et al., 2017). In theory, managers could imperfectly target regulation (e.g., access bans) at non-locals, who tend to be weaker swimmers and have less familiarity with the sandbar, but in practice identifying non-locals and enforcing these laws would likely be impractical, not to mention politically unpalatable. Even in cases where it is reasonable to target policy along the relevant margin, some other latent source of heterogeneity may hinder this management effort. For example, the Canadian Department of Fisheries and Ocean (DFO) enacts and enforces different fishing regulations on indigenous and non-indigenous (recreational) salmon fishers on the Fraser River in order to uphold the Canadian Supreme Court's ruling that indigenous fishers have priority access to salmon as a constitutional right (Nguyen et al., 2016). While the DFO's policies address the difference in cultural values that each group gets from fishing salmon, they fail to address differences in the groups' fundamental beliefs about how and by whom the salmon stock should be used, spurring periodic violent conflicts between RU groups.

Apart from amplifying dilemmas, RU heterogeneity also often plays a role in driving management outcomes. Jungers et al. (2023) find that the degree to which recreational fishers in the U.S. Gulf of Mexico approve of a theoretical switch in how red snapper harvest is rationed (i.e., from a combination of season closures and bag limits to year-round retention and per-fish retention fees) significantly impacts their behavioral responses to said intervention. However, "approval" is not a targetable margin of heterogeneity, which means fisheries managers would have to grapple with the consequences of this latent difference should they ever choose to move forward with the proposed policy.

Another example of latent heterogeneity complicating management efforts comes from my case study in Chapter 4. The National Park Service (NPS) offers a bounty for brown trout in the Lees Ferry fishery to encourage recreational fishers to remove more of those fish from the river. The fishers with the capacity to catch the most brown trout per trip, on average, are those on guided fishing trips (likely because they are able to leverage the guides' superior local knowledge.) However, some unobservable source of heterogeneity (likely a catch-and-release value ethic) prevents guided anglers from participating in the program, which undermines its efficacy. Offering guided fishers a larger bounty payment in an attempt to overcome this reluctance to participate would be politically fraught and likely ineffective at overcoming this value-based barrier to participation. Alternately, NPS could target informational campaigns at guided and unguided anglers to address their different barriers to participation. For example, a two-prong information campaign that teaches unguided anglers how to effectively catch Lees Ferry brown trout while convincing guided anglers that controlling the brown trout population is more important than preserving their catch-and-release ethics could potentially make the incentive program more effective.

RU heterogeneity may also influence the distributional outcomes of management interventions. For example, Kubo and Shoji (2016) explain that two RU groups at the Numameguri Hiking Trail have different values for bear sightings, and are therefore differentially harmed by policies designed to protect hikers by distancing them from bears.

One additional challenge that RU heterogeneity introduces to the management space is that even if it is observable, managers may not identify it as important if it is correlated with an "invisible" dilemma. In the case of the WWBR, had researchers and park managers failed to notice that Chinese and Turkish immigrants were underrepresented in the user base, then even though heterogeneity in race, ethnicity, and immigration status are relatively easy to see, the dilemma with which they correlate (CGT) would have gone unrecognized and unaddressed (Höglhammer et al., 2019).

2.5.1.2 Dilemma Visibility

Recreation managers can target interventions only at dilemmas that are visible to them, so understanding what factors determine visibility could help those managers recognize what types of dilemmas may exist in their systems that they cannot immediately see. I discuss various contributors to dilemma visibility in the following sections.

2.5.1.2.1 Management Mandates and Capacity

One common cause of dilemma blindness is insufficient monitoring capacity, which is determined by available funding, the managing agency's mandates, and characteristics of the system's RU, NI, and PI. In the United States, recreation funding has not kept pace with the increasing demand for outdoor recreation, which means recreation managers have less money to devote to monitoring their systems for emergent dilemmas (Watkins, 2019). Furthermore, recreation managers must devote their limited funds toward monitoring for the subset of system elements, processes, and outcomes outlined in their mandates. In other words, the way that an agency's management mandates define success and for whom (i.e., for NI, for all RU, for particular RU groups, etc.) determines what those managers monitor and the dilemmas that are visible to them. Managers with multi-use mandates that include promoting both recreation and conservation may be more likely to monitor for both RU fulfillment and NI integrity than managers whose sole mandate is to conserve NI. For example, the BLM in the U.S. and the Ministry of Environment in Japan have multi-use mandates, and the problems identified in the cases for which those agencies were managers focused on conserving NI while maintaining mostly uninhibited access to high quality recreation opportunities (Kubo & Shoji, 2016; Spaul & Heath, 2016). In Spaul and Heath (2016), the BLM's mandate to promote tourism is likely responsible for the influx of newcomers that eroded the legacy *dunes culture* at the St. Anthony Sand Dunes, causing HOP to emerge. So mandates may not only create a blind spot surrounding an existing dilemma, but they may also prevent managers from anticipating dilemmas that may emerge from their own policies and interventions.[18]

In contrast to those two multi-use agencies, the Yunnan Province Forestry Bureau's (YPFB) primary objective is to conserve NI within National Nature Reserve protected areas. Accordingly, YPFB's management strategy has been to ban hunters from those regions with little consideration of other incentives hunters face that might lead them to ignore the hunting bans and even develop information-sharing processes to dodge enforcement (Chang et al., 2017).

Finally, the nature of the RU, NI, and their fundamental recreation processes make certain systems relatively more difficult or costly to monitor. The St. Anthony Sand Dunes and the coastline of Miscou Island are wide expanses with innumerable access points that facilitate spreading out of RUs (Hogan et al., 2021; Hughes & Paveglio, 2019). These traits make these systems more difficult to monitor than the Brigantine Natural Area Beach with its limited width and single access point (Burger & Niles, 2014).

2.5.1.2.2 Speed of Emergence

Both fast and slow-emerging dilemmas pose unique challenges for detection. Some dilemmas are "invisible" because they have not yet impacted the system in question. In other words, slow exogenous changes increase the probability of certain fast exogenous shocks to recreation-hosting systems.

[18] It is worth pointing out that multi-use mandate agencies are sometimes not given funding proportional to their mandates, which also impacts which dilemmas are visible to them.

It is difficult to manage for probabilistic shocks, even those that are likely or that would significantly or permanently impact the system's endogenous processes and outcomes. Knowing that zoonotic pandemics and coral bleaching events will occur more frequently in the future does not necessarily make their impacts on RUs (beachgoers, fishers, scuba divers, etc.) or the NI with which they recreate easier to anticipate and manage (see Pereira et al., 2021; Weijerman et al., 2018).

Even though it is difficult to anticipate when pandemics, severe weather events, droughts, oil spills, floods, and other sudden anthropogenic shocks will occur, it is important that an SES be resilient to those shocks. Carpenter et al. (2015) show that tightly managing an SES for consistency of outcomes may undermine its adaptive capacity, and thus its resilience to sudden exogenous shocks. Anderies et al. (2019) build upon this finding and show that system managers should invest in a portfolio of management tools to address uncertain or unanticipated potential contexts or shocks.

Modeling is a powerful and important tool for building that portfolio of management tools. Forward-looking models allow managers to investigate how potential shocks or interventions might change their systems' equilibria according to their particular characteristics and processes. For example, Jungers et al. (2023) estimate forward-looking models of recreational fisher behaviors in response to a prospective policy change, then use those parameterized models to simulate a range of fiscal, economic, and biological outcomes of that proposed policy. They find evidence that the establishment of a market for red snapper quota between headboat anglers and commercial harvesters may result in quota flowing toward the commercial sector, in contrast to the current narrative that recreational anglers have higher marginal values for harvest. Such a counterintuitive finding would not have come to light without this *ex ante* modeling endeavor.

Bioeconomic models that explicitly incorporate RU decision-making processes and NI dynamics are increasingly popular (especially in the realm of recreational fisheries) and incredibly powerful tools for exploring how the full set of system feedbacks and outcomes equlibrate in response to exogenous shocks or endogenous management efforts (e.g., Lee et al., 2017; Massey et al., 2006). Finally, a growing body of literature reveals the importance of explicitly accounting for RU heterogeneity in these bioeconomic models (Fenichel & Abbott, 2014; F. D. Johnston et al., 2010).

Dilemmas that emerge slowly, either exogenously or from endogenous processes, pose a different core management challenge than fast dilemmas. While slow changes usually do not necessitate immediate management intervention, the gradual nature of their emergence may make them harder to identify until a critical threshold or tipping point is reached. A good example of a slow exogenous change is the gradual increase of newcomers who eroded the *dunes culture* and caused the emergence of HOP at the St. Anthony Sand Dunes (Hughes & Paveglio, 2019), while the "disengagement tipping point" identified by K. M. Brown (2016) where mountain bikers abandoned their responsible use norms in response to repeated negative encounters with other RU groups is an example of slow endogenous emergence.[19]

Consistent monitoring of NI and RU may be necessary to catch slow-emerging dilemmas. The case study in my fourth chapter came about because consistent monitoring of fish stocks, RU experience outcomes (i.e., catch rates), and water temperatures alerted Lees Ferry managers that the fishery is likely in the midst of a transformation whose outcomes, while uncertain, include a non-insignificant probability of harm to a native, endangered species (Runge et al., 2018). This case illustrates

[19]The disengagement tipping point for RUs is analagous to the well-studied issue of sudden state-shifts in NI, the most well-known example of which is eutrophication in shallow lakes (Carpenter et al., 1999; Scheffer et al., 2001).

the value of pairing data collection and system modeling efforts in identifying and managing slow-emerging dilemmas.

2.5.1.2.3 Mediating Feedbacks

In some cases, a dilemma may be hidden by some equally invisible mediating or negative feedback loop. Just because these mediating processes are hidden, however, does not mean they are not vulnerable to shocks or cannot fall victim to a well-intentioned management intervention. In the examples I found, these mediating feedbacks are the result of a collective action agreement between members of a particular RU group that is designed to mitigate their impacts on NI or on other RU groups to ensure continued high-quality recreational experiences for themselves and others into the future. Before they reached the "disengagement tipping point," mountain bikers in Cairngorms National Park maintained responsible use norms through link 6 that mediated their riding behaviors (i.e., that pushed them to maintain trails and yield to pedestrians even when that would ruin the flow of their run) through link 5 (K. M. Brown, 2016). Similarly, legacy ATV riders at the St. Anthony Sand Dunes maintained a *dunes culture* (via link 6) of responsible and safe riding behavior that prevented HOP from arising for many years (Hughes & Paveglio, 2019). It is important to understand under what conditions this type of collective action may arise and the conditions under which it may dissolve both to identify dilemmas that may be lurking and to avoid creating new dilemmas through management actions.[20]

[20] For a more complete discussion of the conditions that give rise to and dissolve collective action arrangements, see Ostrom (1990) and others.

2.5.2 A Portfolio of Interventions

I now turn my discussion to identifying circumstances under which different intervention approaches are more or less effective. Managers of different disciplinary backgrounds and with different mandates will naturally gravitate toward different types of interventions. For instance, natural scientists or managers whose primary mandate is NI conservation may be more attracted to link 4 solutions (e.g., habitat restoration, culling invasive species, etc.) or link 5 solutions that involve physically separating RU from vulnerable NI (e.g., fencing off nesting habitat in Burger and Niles (2014) or imposing ATV-specific trail closures during Golden Eagle mating season in Spaul and Heath (2016)). Social scientists or managers whose mandates prominently feature recreation, on the other hand, likely prefer link 5 interventions designed to mediate incentive-driven behaviors (e.g., gear restrictions to lessen the impact of hunters or fishers) or "nudges" targeted at changing incentives via link 6.[21] By engaging in the following discussion, I hope to emphasize the importance of considering the full range of potential interventions.

2.5.2.1 Link 4: Modify NI

Modifying NI through link 4 could take many forms, including installing HHMI to either dissuade high-impact RU behaviors (e.g., putting debris on satellite camp pads in Eagleston and Marion (2017)) or to reverse or build resilience to NI change (e.g., nourishing beaches or, as was suggested by Eagleston and Marion (2017),

[21]"Nudge" refers to the concept from behavioral economics where managers use policy or information and outreach to alter peoples' decision making by tweaking their choice set (Thaler & Sunstein, 2003, 2009).

replacing eroded soil at official camp pads); cleaning up pollution or litter; stocking or transplanting flora and fauna; performing habitat restoration; or culling invasive species.

My comparative analysis generates two key lessons relevant to link 4 interventions. First, they are not done in isolation, and instead have the potential to modify system processes in ways that are both intentional and unintentional. Link 4 interventions may cause or amplify clockwise secondary dilemmas, as the direction of modification or information sharing is from PI to NI to RU. Thus, it is imperative that managers looking to implement link 4 interventions consider how RUs will perceive and respond to any changes to NI. Interventions designed to redirect RU efforts may be ineffective if the modifications are not binding on RU behaviors and there is a lack of buy-in. For instance, beachgoers in Pará were not convinced it was important to socially distance themselves, and so chose to ignore the spacing and group sizes suggested by table and umbrella (HHMI) installations (Pereira et al., 2021).

The second lesson is that the link 4 modification itself may cause unintended and unacceptable levels of change to the NI. This lesson is more obvious in contexts like building a new dam, modifying waterways, and building roads through key habitat, but is less obviously applicable in instances of relatively minor interventions. For instance, the managers who called for or allowed the installation of marinas in the Mediterranean Sea likely did not anticipate that HHMI would facilitate the spread of aquatic invasive species (Martínez-Laiz et al., 2019). Similarly, the managers who trim back willow grasses and compact the snow over them to build ski trails at Cucumber Gulch every winter likely did not anticipate their minimal modifications would create habitat and opportunity for invasive species intrusion (Carello et al., 2018).

2.5.2.2 Link 5: Mediate the RU - NI feedback

Link 5 interventions are usually designed to limit the impact that RUs have on NI by limiting access or intensive use (i.e., partially enclosing the commons), reducing individual RUs' ability to impact NI (e.g., through gear or technology restrictions), and declaring spatially or temporally-defined closures to protect NI where and when it is most vulnerable to disturbance.

The partial enclosure of a recreational commons can be achieved either through putting a price on recreational access to limit quantity demanded, or by directly capping the number of RUs or the intensity of their NI use. Economists have long favored price-based interventions, including the implementation of congestion pricing (G. Brown, 1971; Cesario, 1980), access fees (i.e., parking, license, or gate fees) (Holmes & Englin, 2005; Richer & Christensen, 1999), or per-unit fees on intensive use (Jungers et al., 2023). The popularity of price-based interventions among economists stems from the theoretical efficiency gains that can result by allocating resources to those with the highest value, thereby solving a problem of how to "ration" use (Holzer & McConnell, 2014).

Depending on how they are implemented, price-based interventions can run up against issues of political palatability or concerns about equitable access.[22] Modeling these interventions in the context of specific systems can help managers anticipate these and other potential implementation challenges that may or may not be covered by their management mandates.

Quantity-based interventions may be direct (i.e., letting only a limited number

[22]For a discussion of the efficacy-equity trade-off in pricing environmental goods, see e.g., Baranzini et al., 2017; Goulder and Parry, 2008; Mansur and Olmstead, 2012.

of RUs through a gated access point, closing a recreational fishery once a certain quantity of fish have been harvested, or allocating a limited number of harvest tags for extractive intensive use) or indirect (e.g., the laws discussed by Pereira et al. (2021) that disallow beach access via public transit, effectively limiting visitation to the number of available parking spaces), and come with their own set of challenges. For instance, limiting recreational access or intensive use on a first-come-first-serve basis inefficiently allocates recreational experiences, which is to say distributes recreational access and intensive use to those who can most quickly or easily access the NI rather than to those who derive the most U from doing so (Holzer & McConnell, 2014). Tradable harvest tags as explored by Jungers et al. (2023) are one way managers can overcome this access-U mismatch under certain system contexts. Once again, system-specific models (such as those estimated by Jungers et al. (2023)) can help managers identify how particular quantity-based interventions might impact the processes and outcomes in their own systems.

Rules designed to limit individual RU's ability to impact NI are ubiquitous in recreational fishing and hunting contexts. Gear restrictions (e.g., bans on barbed fish hooks or on firearms with extended magazines) and daily harvest or bag limits are common tools that managers of public waterways and land employ to limit the amount of impact a single recreational fisher or hunter can have on NI on a given outing. Similar technology bans have been discussed in non-extractive recreation contexts, as well. For example, Mitterwallner et al. (2021) show that mountain bikes with electrical assitance (eMTBs) increase their riders' potential impacts on NI by enabling them to ride further, higher, and for longer. Technology restrictions may be effective in some systems, but it is important to remember that these policies do not cap overall RU impact because they do not prevent the technology-constrained RUs from taking more recreation trips or new RUs from entering the system (for further discussion set in a recreational fisheries context, see Cox et al., 2002). Therefore, technology restrictions may need to be paired with price- or quantity-based access restrictions to effectively limit pressure on NI.

One additional wrinkle is that the most high-tech recreation mode will not necessarily be the one with the highest NI impact. For example, Spaul and Heath (2016) found that pedestrians—with their slow, unpredictable movement patterns—are more likely to disturb nesting eagles than the faster, more predictable movements of ATV riders.[23] So recreation managers considering technology restrictions should carefully consider whether such policies will be effective under the specific RU and NI contexts of their system.

Finally, managers may limit RU impact via link 5 by using HHMI and SHMI to spatially and temporally distance RUs from particularly vulnerable elements of NI. For instance, the New Jersey Department for Environmental Protection maintains a fence around key habitat for migrating shorebirds in the Brigantine Natural Area (Burger & Niles, 2014), while hunting in ecologically-important protected areas is illegal in China's Xishuangbanna Dai Autonomous Prefecture (Xishuangbanna) (Chang et al., 2017). These interventions are only effective if there is sufficient RU buy-in or enforcement to ensure compliance. For example, hunters in Xishuangbanna do not comply with the hunting bans, and avoid enforcement through information-sharing (Chang et al., 2017). So these interventions may be ineffective in systems with limited monitoring and enforcement capacity unless managers can convince RUs to abide by those laws. I discuss some potential methods for increasing buy-in via link 6 in the next section.

[23]This finding echos that of a dissertation chapter by Spahr (1990).

2.5.2.3 Link 6: Appeal to RUs

Link 6 interventions are where the PI seeks to influence recreational processes or outcomes by acting upon or appealing directly to the RUs. In general, PI can either use rewards or information to incentivize particular RU behaviors, or they can limit or ration extensive recreational access.

McCreary et al. (2019) suggests providing information on how to adapt to weather shocks to prevent older and lower income RUs from leaving the Lake Superior system at a disproportionately high rate, while, in the case from my fourth chapter, NPS offers fishers a monetary incentive (i.e., a bounty) to remove invasive brown trout from the Lees Ferry fishery. However, information or incentives alone may not be sufficient to induce desired recreational behaviors. In Chapter 4, for example, I find that an NPS bounty program under performed relative to its stated goals because the monetary incentive was insufficient to overcome logistical or value-based objections to retaining fish for the representative Lees Ferry angler. In that chapter, I speculate that an information campaign designed to make willing participants more effective at catching brown trout could improve the program's performance. More generally, pairing information and incentive campaigns may increase their efficacy at inducing desired behaviors, especially if they can work together to weaken any countervailing incentives the RUs may face.

Gstaettner et al. (2017) show that information campaigns can fail because RUs are skilled at overcoming cognitive dissonance in ways that are hard to anticipate, which may make information campaigns ineffective or counterproductive. A popular narrative amongst Mersey Point visitors is that those who drown crossing the sandbar tend to be poor swimmers—a fact that even weak swimmers use to convince themselves that crossing the sandbar carries little risk for them, personally. Similarly, the lifeguards that the Department of Parks and Wildlife stations along the sandbar to signal risk instead make RUs feel safer to cross. Thus, Gstaettner et al. (2017) recommends tying information to counter-narratives (e.g., an example of a strong swimmer drowning) to bolster the information's efficacy.

Information or narrative campaigns may also be used to build empathy between disparate RU groups (K. M. Brown, 2016; Nguyen et al., 2016). Whatever the information campaign's goals, surveying RUs or incorporating them in the management process are two ways of ensuring that any information that is disseminated is salient to its intended recipients and doesn't yield unintended consequences. For example, Höglhammer et al. (2019) suggest consulting RUs from different cultural groups to ensure all information about recreation in the WWBR is multi-lingual and presented using phrasing that resonates with each target community, while Hughes and Paveglio (2019) recommend leveraging the local knowledge and experience of legacy RUs by incorporating them into the decision-making processes surrounding the St. Anthony Sand Dunes. Chang et al. (2017) find that the current approach of turning local informants in Xishuangbanna does not increase compliance with hunting bans, and only creates cycles of revenge. Instead, the authors suggest that transferring governance of hunting from national agencies to individual villages may increase buy-in and compliance.

In addition to providing information and offering incentives, PI may choose to ration recreational access on the extensive margin. In other words, system managers may try to limit who or how many RUs are accessing NI for recreation. In extractive recreational contexts, managers often ration extensive access by requiring the purchase of hunting and fishing licenses. Similarly, NPS and managers of state and local recreation areas commonly charge access fees to ration access. For NI that is in high-demand and/or that is particularly vulnerable to RU disturbance, managers may either disallow or set limits on the number of RU that are allowed to access the NI.

The cases I compared in this archetype analysis tended to omit discussions regarding limiting extensive use. This omission may suggest an implicit assumption that RUs should not be prevented from accessing NI, whether for reasons of ethics or political palatability. In any case, access rationing is a popular tool of resource managers globally, which indicates it is an important family of interventions within the broader management portfolio.

2.6 Conclusion

This chapter presents an initial exploration of the dilemmas faced by managers of nature-based recreation. I show that these dilemmas and the interventions designed to address them do not exist in isolation. Rather, they are embedded in complex SES, and are therefore part of a dynamic loop of dilemmas followed by interventions, followed by further emergent dilemmas, and so forth. Both the co-evolving problem space and management structure of any given system may come to a dynamic equilibrium, but anticipating what that equilibrium may look like (i.e., what the system processes and outcomes will be) is tricky. Furthermore, this comparative analysis is purely descriptive; it cannot make normative prescriptions for particular systems or system types. For both of these reasons, modeling efforts that account for the full set of potentially salient system feedbacks and can thus generate normative, system-specific insights will be an increasingly important management tool as we progress through the Anthropocene, and the nature of the endogenous processes and exogenous shocks that managers face continues to evolve.

The types of system-specific models that I recommend will depend heavily upon high-quality data collection efforts or well-supported and interrogated assumptions regarding system characteristics. But more than that, these modeling efforts should incorporate an empirically-informed understanding of how different intervention approaches tend to succeed or fail at meeting their stated aims, as well as the types of secondary dilemmas that they may cause. The archetypes I identify in this chapter are a good starting point for future modeling efforts, but the sample of cases I use to construct this preliminary typology is small. Future efforts to compare additional cases are needed to refine these archetypes and improve their usefulness for system managers and researchers.

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Chapter 3

À LA CARTE MANAGEMENT OF RECREATIONAL RESOURCES: EVIDENCE FROM THE U.S. GULF OF MEXICO

3.1 Abstract

Externalities from recreation scale at both the extensive and intensive margins of resource interaction. Recreators have differentiated demands for these margins, so unbundling the prices of access and intensive depletion could improve upon traditional management. I use choice experiment data from US Gulf of Mexico recreational headboat anglers to estimate structural models of trip and red snapper retention demand, then simulate aggregate harvest across a range of trip and harvest tag prices. In my simulations, the red snapper harvest tag market equilibrates at $15 per tag and generates $760,000 in management revenues per year while more efficiently allocating harvest.

3.2 Introduction

Outdoor recreation plays an important role in the lives of North Americans and in the United States economy; an estimated 97% of U.S. citizens aged 16 and older engage in outdoor recreation at least once in any given year (Interagency National Survey Consortium, n.d.). In 2019, outdoor recreation accounted for $459.8 billion (2.1%) of U.S. current-value GDP, and the sector's growth rates for real output, compensation, and employment levels were faster than those of the average sector

(Bureau of Economic Analysis, 2020). Federal and state natural resource managers face two foundational challenges in facilitating sustainable recreational use: 1) the management of the impacts on natural capital from recreational use; and 2) the problem of funding resource management activities when state support is often scarce.

Outdoor recreation frequently degrades the natural capital on which it depends, whether as an objective of the activity itself (e.g., fishing and hunting) or as a side-effect of ostensibly non-extractive uses (e.g., erosion from trail degradation or fire risk from human use). In the absence of effective management, these externalities may lead to excess resource degradation, with implications for both the quality of the ongoing recreational experience and the sustainability of ecosystems.

Federal and state resource managers have the unenviable task of containing the externalities of recreation, which arise at both the extensive margin (i.e., with the number of individuals accessing the resource) and the intensive margins (i.e., the per-trip level of resource impact), even as maintenance backlogs pile up and their future funding becomes ever more uncertain.[24] Wildlife agencies and other public land and waterway managers have historically received revenues from hunting and fishing license and equipment sales (Lueck, 2000), and in 2017, 35% of funds for conservation were from state license sales (Voyles & Chase, 2017). In that same year, the second and third largest sources of conservation funding, the federal Pittman-Robertson and Dingell-Johnson Acts, contributed only 15% and 9% of total conservation funding, respectively (Voyles & Chase, 2017). Adult hunting and fishing participation are projected to decline 11-12% and 2-3% by 2030 (White et al., 2016), which means that the largest source of conservation funding—license sales—may be at risk.

[24]Vincent (2019) estimates that, in fiscal year 2018, the Bureau of Land Management, Fish and Wildlife Service, National Park Service, and Forest Service had a total estimated maintenance backlog of $19.38 billion.

Resource managers occasionally address environmental impacts of recreation by directly regulating the quantity of natural capital consumed (i.e., output-based management). For instance, game managers may directly control harvest by allocating a limited number of harvest tags for trophy species. However, it is far more common to address spillovers indirectly by trying to limit *inputs* to the impact. Park managers may place quotas on visitation to fragile backcountry habitats, while managers of sport fisheries attempt to curb the quantity and impacts of recreational "effort" through a combination of gear restrictions, retention (bag) limits, and seasonal closures. These input-based policies, while sometimes effective at containing the impacts of recreation, do not address the individual incentive to overuse a resource, because they do not directly encourage recreators to internalize the full marginal cost of their activities. As a result, recreational decisions—from the decision of how many trips to take to how many fish to retain vs. release—can be distorted, with the result that recreational experiences and the recreational consumption of natural capital itself is inefficiently allocated (Holzer & McConnell, 2014). Furthermore, input controls (at least as commonly implemented) are not revenue-raising, so that externality control, while costly, contributes little or nothing to the coffers of resource management agencies.

For these reasons, economists have often recommended full marginal cost pricing policies to address externalities. G. Brown (1971) and Cesario (1980), for example, emphasize the importance of accounting not only for marginal operating costs, but also peak-time or congestion spillovers when valuing and pricing a recreation site and its substitutes. Yet, the practice of closely tying the effective price paid by a recreator to their consumption of scarce (including environmental) resources remains rare. Empirical research to guide such endeavors is similarly sparse, and has primarily focused on the potential for access fees, perhaps in combination with an annual license or permit, to balance normative revenue and equity objectives (Richer and Christensen, 1999; Williams et al., 1999; Holmes and Englin, 2005; Abbott and Fenichel, 2013). The literature has not considered the implications of unbundling the price of access and the price of consumptive use of scarce recreational resources.

I examine the potential for a differentiated, "a la carte" management approach to better capture users' heterogeneous marginal values of access and consumption relative to other second-best regulatory pricing policies using the case of the US Gulf of Mexico (GOM) recreational headboat fishery.[25] In general, recreational resource users derive utility from both experiential and consumptive trip attributes. Recreational anglers, in particular, increase their utility by selecting a fishing experience, which is priced in a market for headboat trips, and by directly consuming an environmental good (fish) in the course of that experience. This headboat fishery, therefore, is an ideal context for exploring whether unbundling the prices of experience and consumption could improve allocative efficiency.

Output-based "a la carte" management in the headboat sector could take a few different forms. For instance, access to fishing trips might be regulated through a limited entry permitting system for vessels and market-driven trip pricing (as currently) coupled with a government-levied fee for fish retention. Alternatively, harvest could be regulated through the allocation of a limited number of, potentially transferable, harvest tags to anglers (Abbott, 2015; R. J. Johnston et al., 2007). Per-fish retention fees and harvest tags are economic duals; retention fees indirectly restrict harvest by increasing the cost of retaining a fish, while harvest tags directly limit harvest. Assuming harvest tags are distributed using a market mechanism (e.g., if tags are sold

[25] Headboats or party boats have permits to take 15 or more fisherman to fish for reef fish in the exclusive economic zone of the US GOM. These vessels typically charge anglers "by-the-head" to take an offshore fishing trip.

by brokers or are allocated and tradable in a frictionless market), then the market price for a harvest tag should equal the per-fish retention fee that results in the same number of fish harvested as tags distributed.

In this paper, I use choice experiment data from an online survey of anglers who took deep sea fishing trips onboard headboats in the US GOM to investigate anglers' behavioral responses to and the revenue-generating potential of trip pricing that decouples resource consumption (harvest) from the trip itself. By using stated preference data, I am able to assess behavioral responses to a range of pricing policies that do not currently exist.

Respondents in my choice experiment data were presented with a two-part tariff of trip prices and per-fish retention fees as an alternative to the status-quo of trip prices with bag limits. I estimate structural models of extensive (trip-taking) and intensive (per-trip retention) margin behavioral responses to a change from bag limits to retention fees for red snapper. I then show how these two models can be used to perform *ex ante* behavioral analyses of trips demanded, fish harvested, and revenues generated for a variety of policy counterfactuals. Because retention fees and marketable harvest tags are economically equivalent, I interpret my policy simulations in terms of harvest tags, even though the survey on which my models were based asked respondents about retention fees. I explain my choice to focus on harvest tags in section 3.6.2.

In the next section, I provide some context both on recreational fisheries management, generally, and on the US GOM recreational red snapper headboat sector, specifically. Then, in section 4.4, I explain how my data were collected, cleaned, and weighted. In section 4.5, I build my extensive margin model of trip demand and my intensive margin model of per-trip red snapper retention demand, and then explain how I calibrate those margins together for my policy simulations. I analyze and discuss both models plus the resultant simulations in section 4.6.

The trip taking model shows that anglers are more likely to take trips with lower trip prices and lower per-fish retention fees, as well as higher expected catch of fish other than red snapper and higher expected catch of red snapper that they are allowed to retain. Additional red snapper caught that must be discarded under a bag limit do not impact trip-taking, which suggests that replacing the bag limit constraint with retention fees may be welfare improving. I also find that replacing a bag limit with retention fees does not impact the probability of opting-out of a trip along any particular demographic margins, and that anglers may even be agnostic between trip prices and maximum expected fee bill (i.e., trip price plus the retention fee times the number of red snapper the angler expects to catch on a given trip) when deciding to take a fishing trip. Furthermore, anglers retain fewer fish at higher retention fees, and become fee elastic in their within-trip retention demand when they must pay more than $56 to retain a red snapper.

In section 3.6.2, I calibrate my trip-demand and per-trip retention demand models together to predict aggregate harvest demanded and revenues generated by harvest tag sales across a grid of trip prices and per-fish retention fees. Resource managers can use this simulation tool to back out a demand curve and associated revenues for harvest tags. I show that, under logbook-derived representative conditions, a market for harvest tags would equilibrate at $15 per red snapper on GOM headboats in my sample, generating just over $760,000 in management revenues per year (assuming fixed catch limits based on historic logbook data) while more efficiently allocating harvest and addressing the fishing mortality externality that recreational anglers impose on one another through their fishing behaviors.

3.3 Research Context

3.3.1 Management of Recreational Fisheries

I explore "a la carte" pricing in the case of marine recreational fisheries. Innovation in recreational fisheries management has been relatively slow given the scale of these fisheries' impacts on fish stocks and on the welfare of recreational anglers. Marine recreational fisheries, in particular, accounted for 4% of all marine finfish landings in 2002, and 64% of landings in the Gulf of Mexico (GOM) in that same year were recreational (Coleman et al., 2004). The majority of recreational fisheries are governed as regulated open access systems in which total effort is limited only through technical mechanisms (Homans and Wilen, 1997). As a result, anglers do not have an incentive to preserve stock today to ensure the fishery is available to other anglers in the future.

Managers of open-access fisheries have long sought to restrict effort by imposing size or daily bag limits on fish retained or by reducing season lengths. However, these methods are not effective at limiting total effort. Bag limits may reduce landings in the short-run by capping per-trip retention for current anglers but neither prevents those anglers from taking more trips nor blocks new anglers from entering the fishery (Cox et al., 2002). Furthermore, bag limits may exacerbate harvest spillovers—especially in fisheries with higher levels of discard mortality—by encouraging anglers to high-grade their catch (Woodward & Griffin, 2003).[26] Similarly, imposing shorter fishing seasons provides no incentive to reduce effort, and instead concentrates fishing effort into a reduced number of days (Cox et al., 2002). Fisheries with abridged, intensive fishing

[26] High-grading is when anglers discard lower value fish so that they may retain more high-value fish under a harvest constraint.

seasons suffer welfare losses, both because they are more congested and because they become inaccessible to some time-constrained anglers who would otherwise participate in the fishery (Arlinghaus et al., 2019). For instance, Abbott et al. (2018) estimate that trading season closures for reduced per-angler retention under a rights-based policy in the US GOM red snapper fishery would increase the average angler's welfare by $139 a year. Given that more than 30% of people 16 years and older in the U.S. participate in recreational fishing, the potential scale of welfare loss due to regulated open access management is staggering (Interagency National Survey Consortium, n.d.).

A corollary to these welfare losses is the fact that access to fishing opportunities and fish harvest under season closures is inefficiently allocated across heterogeneous anglers (Holzer & McConnell, 2014). Rather than allocating scarce recreational goods according to their marginal valuation, as for a typical market good, bag limits and season closures create "rationing rules" that allocate recreational goods in ways that may bear little relation to how anglers actually value them. For example, seasonal fishery closures may allow anglers with low willingness to pay (WTP) for a trip to access fishery resources for the simple reason that they happen to be in the region at a particular time of year, whereas others with a high WTP but less flexible schedules are excluded. Similarly, bag limits may allow anglers with low WTP for fish to retain them even as other, relatively high-skill, anglers may value retaining the same fish more highly but are not allowed to do so due to the bag limit. These potential gains from trade are left on the table under regulated open access, suggesting that some sort of price signal, whether through a tax/fee or market mechanism could improve welfare.

McConnell and Sutinen (1979) and L. G. Anderson (1993) extended commercial fisheries bioeconomic models to the recreational context, demonstrating that the negative effect of present-day harvest on future fish stocks must be internalized by anglers in the present so that they will not engage in over-fishing. If resource managers knew the full, intertemporal social marginal cost of harvest, then they could charge all resource users one price for harvest that internalizes any spillovers and efficiently allocates harvest through time and across users. Importantly, if discarded catch suffers positive mortality, then the price must be differentiated across harvest and discards in order to ensure efficiency (Abbott & Wilen, 2009; L. G. Anderson, 1993), a policy that could potentially be implemented via individual transferable quotas or cooperatives in the case of recreational for-hire fisheries (Abbott & Wilen, 2009). Fenichel and Abbott (2014) consider the possibility that such an "output based" policy is infeasible due to prohibitive costs of monitoring discards and landings (or the "inputs" that determine these outputs.) Abstracting from questions of endogenous discard behavior, they show how efficiency can be improved relative to the unregulated case by levying differentiated trip fees along observable correlates of fishing mortality such as distance traveled, age, income, or fishing tackle and/or mode. Nevertheless, this approach is second-best due to an imperfect mapping between *ex ante* predictions of individual fishery impacts based on observable factors and the realized fishing mortality.[27] The extent of inefficiency declines as the correlation between the observable heterogeneity used to target fees and realized fishing mortality per trip increases.

Given the shortcomings of status-quo management in recreational fisheries, it is plausible that even clearly second-best forms of output-based policies could improve

[27]"Second-best" refers to a social welfare maximizing outcome under binding information or policy constraints.

allocative efficiency, better regulate fishing mortality, and support revenue-raising goals (Abbott, 2015). R. J. Johnston et al. (2007) suggest that harvest tags may be a feasible way to control harvest by assigning short-term, seasonal harvest rights to recreational anglers. Similar to tags frequently used in game management, harvest tags are limited in number and may be allocated through market mechanisms such as auctions and resale provisions to optimize efficiency or raise revenues. In this case, the market also provides a clear signal of the implicit regulatory price of harvest – creating a clear duality between quantity and price-based management. Alternatively, tags can be allocated through some combination of lotteries and set-asides in order to achieve distributional objectives (R. J. Johnston et al., 2007). Harvest tags are capable of achieving first-best efficiency if the number of tags is optimally set, perfectly enforced, and if all discarded catch survives. However, their efficiency is potentially compromised by high-grading behavior under positive discard mortality (R. J. Johnston et al., 2007). In this latter case, it is an empirical question whether harvest tags or alternative forms of management will be more efficient. The high-grading concern is also present in commercial fisheries where total catch is imperfectly observed. Regardless, ITQ fisheries tend to be more efficient than their baseline under regulated open access management.

3.3.2 The GOM Headboat Fishery

Red snapper is a favorite target of recreational anglers in the US GOM and is among the top 10 recreationally-landed saltwater species in the United States (Figueira & Coleman, 2010). The GOM recreational red snapper fishery extends from Texas through Southwest Florida and is accessed both by private boat anglers and by a for-hire sector of over 1300 vessels, most of which are charter boats and 72 of which are headboats (National Marine Fisheries Service Southeast Regional Office, 2015).

In 1988, GOM red snapper was declared overfished and subject to overfishing due to combined stock pressure from the commercial and recreational red snapper fisheries, as well as excess bycatch of red snapper by the commercial shrimp fishery. In the years that followed, NOAA required shrimp fishermen to install devices on their trawl nets that reduced bycatch of juvenile red snapper. The commercial and recreational red snapper fisheries were subject to seasonal and daily harvest caps, as well as gear and minimum size restrictions, and both the commercial and for-hire recreational sectors were accessible through a limited number of licenses. In 2007, the commercial fisheries transitioned to IFQ management with year-round federal seasons. In response to these rebuilding efforts, the catch per unit effort (CPUE) and size of red snapper increased. The increased CPUE induced additional fishing trips (i.e., effort), even as larger fish more quickly exhausted biomass-delimited harvest caps. These two trends paired with extended state seasons that further depleted the available total recreational quota meant federal seasons for the recreational sector needed to be cut ever shorter, even as the stock recovered. In 2014, the season for recreational red snapper fishing was just nine days long, and the accelerating race to fish sparked disputes between the commercial and recreational sectors (Abbott, 2015; Gulf of Mexico Fishery Management Council, 2013; South Atlantic Fishery Management Council, 2017). Even with regulators' efforts to control recreational harvest through abridged seasons, the recreational sector exceeded its harvest cap every year from 2007-2013, except during the 2010 Deepwater Horizon oil spill.

In 2014 and 2015, a subset of the headboat sector opted into a two year rights-based management pilot program called the Gulf Headboat Collaborative (GHC).[28] As in a commercial fishing cooperative, participating headboat owners were allocated red snapper and gag grouper quota to trade amongst themselves according to each vessel's 2011 landings. In exchange for adhering to their quota allocations, GHC participants were exempt from federal red snapper seasons, and could offer year-round retention for their clients. GHC clients still faced daily bag limits of two red snapper during federal seasons, and most GHC captains imposed a one fish bag limit on their clients outside of the federal season in order to stay within their quota allotments. The GHC program increased access to red snapper over a much longer season and number of anglers while remaining within binding harvest limits. It also reduced regulatory discards and increased industry profits (Abbott & Willard, 2017).

3.4 Data

Anglers who took deep sea fishing trips aboard GHC vessels in 2014 and 2015 were asked to fill out an onboard survey at the conclusion of their trip. The GHC vessels hail from 8 ports in Panhandle and Southwest FL, AL and TX and represent the diversity of the headboat market well, with some vessels operating out of well-known tourist destinations (e.g., Clearwater and Destin, FL) and others operating in more remote areas (e.g., Pt. St. Joe, FL and Dauphin Island, AL). As a condition of their participation in the pilot program, vessels were required to make the onboard survey available to all passengers throughout the two-year policy experiment. Therefore, the

[28] Nineteen of the 72 headboats participated in the GHC in one or both years of the pilot.

sampling effort was approximately constant across vessels and across seasons within the year.

In the brief onboard survey, anglers were asked to provide feedback on their trip experience, some sociodemographic information (including age, income, gender, zip code, and saltwater fishing experience and avidity), and their email address if they were willing to participate in a follow-up survey.[29] Around 50% (5,330 out of 10,719) of those who completed the onboard survey provided a valid, unique email address for follow-up. The primary value of the onboard survey in my analysis is to identify and control for differences in characteristics between respondents to the online choice experiments and the the population of anglers taking trips on GHC vessels. An online follow-up survey was sent to those 5,330 email addresses in two waves in order to minimize recall bias (December 2, 2015 through December 22, 2015 and February 11, 2016 through March 7, 2016).[30,31] The response rate for both waves was 15%, with a total of 813 respondents, after excluding 10 surveys due to missing information or unreasonable trip recall responses.

Two versions of the online survey were distributed—one that focused on red snapper as a target species and one that focused on gag grouper. my data includes only those 537 surveys that focused on red snapper. Of those anglers included in my final dataset, 34% live in the GOM region year-round, 16.57% belong to an angler organization, and 83% are male. The average respondent is 49.45 years of age ($sd = 13.56$), has 16.87

[29]Anglers who provided their email were entered into a drawing for a free fishing trip.

[30]In order to ensure the wording and experimental design of the internet survey were effective, two focus groups were conducted with local anglers in Pensacola, FL in August 2015. A pretest of the online survey was conducted in October 2015 and received 39 responses.

[31]The full survey can be accessed at http://wpcareyschool.qualtrics.com/jfe/form/SV_7ZMU08RRoqoSkF7.

years of experience fishing in the US Gulf of Mexico ($sd = 15.14$), and has an annual household income of nearly \$108,000 ($sd = \$60.46$).[32]

There were five sections to the online survey. In the first section, respondents were asked about their vacation and recreational activities over the past year, as well as their degree of familiarity with the GOM. The second section had anglers report how many headboat trips they took in the previous year, and asked them to recall some characteristics of those trips. The remaining three sections were presented to respondents in randomized order and I use data from one of these sections that included a choice experiment.[33]

In the choice experiment, respondents were first introduced to a hypothetical per-fish retention fee as an alternative to traditional bag limits. In two different experimental arms, individuals were told either that any retention fees paid would be retained by the headboat captain or that they would be invested in conservation or research within the fishery.[34] Respondents then rated the fee-based program from "definitely acceptable" to "definitely unacceptable" (see Figure 4). In my final sample, 34.82% of respondents said retention fees were a somewhat or definitely unacceptable alternative to bag limits, while 47.67% said those fees were somewhat or definitely acceptable.[35] Following this fee acceptance question, anglers were then presented a

[32] 7% of respondents in the final sample failed to provide household income data, while 18% did not provide data on the number of years of fishing experience in the GOM. Lloyd-Smith et al. (2019) impute the missing income and experience data with multiple imputation using chained equations (MICE), and I included this imputed data in my summary statistics.

[33] The other two sections asked contingent trip behavior and time valuation questions, respectively, and are utilized in other research (Abbott et al., 2018; Lloyd-Smith et al., 2019, 2020).

[34] Exactly 50% of respondents in my final data received each of the two treatment arms.

[35] The remaining 17.51% of respondents said replacing the status quo bag limit with retention fees was neither acceptable nor unacceptable.

Many recreational fisheries, including red snapper, are managed through bag limits to help ensure the fishery is not depleted. An alternative management option used in some fisheries is where fishermen pay a fee per fish they retain. For the next two choices, assume that there is an alternative fishery management in place where there are no limits on the number of red snapper you can retain (i.e. no bag limits), but rather a fee for each red snapper retained.

The fee would be collected by the headboat operators as people leave the vessel at port. The money collected by the headboat operators would be used to fund habitat enhancement projects in the Gulf of Mexico and Gulf of Mexico fishery research.

How acceptable do you find the fishery management option where there are no limits on the number of red snapper you can retain (i.e. no bag limits), but rather a fee for each red snapper retained?

	Definitely Acceptable	Somewhat Acceptable	Neither Acceptable nor Unacceptable	Somewhat Unacceptable	Definitely Unacceptable
Management option with a fee for each red snapper retained	○	○	○	○	○

Figure 4. Fee Acceptability Question, Showing the Version of the Question where Fees are Used to Fund Research and Habitat Enhancement.

series of four choice scenarios. In one pair of experiments, retention was governed through bag limits, while the other pair featured retention fees. The order in which respondents faced each experimental pairing (i.e., the two bag limit or fee scenarios) was randomized. In each of the four scenarios, respondents were asked to choose between taking one of two fishing trips (with experimentally-varied trip characteristics as denoted in Table 7) or the outside option of not going on a headboat trip (see Figure 5).[36] Anglers were presented with either partial day or full day trip prices throughout their four scenarios. I pool partial and full day trips in my analyses,

[36]The choice experiment experimental design was based on results of the pilot survey. Responses from the pilot survey were used to estimate a conditional logit model and these parameters were used as priors in a D-efficient experimental design for the main survey.

Table 7

All Variable Levels Included in the Choice Experiment Survey.

Features	**Levels**
Total expected number of red snapper caught per trip (*target*)	1, 3, 5, 7
Red snapper bag limit (*retain*)	1, 2, 3
Per-fish retention fee for red snapper (*fee*)	\$10, \$25, \$35, \$50
Number of other species caught per trip (*other*)	1, 2, 4, 6, 8
Vessel is congested? (*congest*)	Spacious, Crowded
Price for half day trip (*price*)	\$50, \$ 80, \$120, \$150, \$200
Price for full day trip (*price*)	\$80, \$120, \$130, \$200, \$250

based on evidence that angler behavior and preferences are not significantly different between partial day and full day trips.[37]

Respondents who indicated they would take one of the two trips on either of the fee version choice scenarios were then asked how many of the red snapper they would retain given the expected catch and the per-fish fee on their chosen trip. I use this contingent behavior data to model the intensive margin of fish retention in response to fees.

[37] I estimate a conditional logit, which includes all regressors (X) from Table 8 and interactions between these variables and an indicator for *fullday*. I then perform a Wald test in which I fail to reject the null hypothesis that all *fullday* interaction terms are equal to zero ($\chi^2 = 9.13$, $p = 0.3318$).

Features	Trip 1	Trip 2	No trip
Total expected number of red snapper caught per trip	1 red snapper	7 red snapper	Do something else, but do not go saltwater fishing on a headboat
Cost per each retained red snapper	$50	$10	
Number of other species caught per trip	8 fish	2 fish	
Congestion	Spacious	Crowded	
Price for full day trip	$80	$200	

I would choose...

Trip 1 ○ Trip 2 ○ No Trip ○

Figure 5. A Choice Experiment Question from the Online Survey in which Respondents Faced Retention Fees.

3.5 Methods

I utilize responses to the trip choice experiments and follow-up retention questions to estimate separate models for both the extensive (i.e., the probability of taking a fishing trip aboard a GOM headboat) and intensive (i.e., the number of fish retained conditional on having chosen to take a trip) margins of demand for retained fish.

I then calibrate those models together in order to simulate total trip and harvest demand across a range of "a la carte" policies.

In order to model trip demand as a function of trip prices and retention fees, I estimate a conditional logit model of individual and alternative-specific characteristics and their interactions on trip choice. Each respondent faced four different choice sets including two bag limit and two fee scenarios, so I group observations by respondent. Underlying each choice for this conditional logit is a random utility model in which individual i chooses to take one of the two trips (j=1,2) presented to them or an opt out (j=3) option. Let the utility of choosing alternative j for individual i in any given choice scenario c be

$$U_{icj} = \begin{cases} \beta' X_{icj} + \varepsilon_{icj} & j = 1,2 \\ \psi' Z_i + \varepsilon_{ic3} & j = 3 \end{cases} \tag{3.1}$$

where X_{icj} indexes the characteristics of each fishing alternative, Z_i are individual-specific characteristics, β and ψ are parameters to be estimated, and ε_{icj} is a stochastic, type I extreme value error term.

The trip characteristics in X_{icj} are the price (i.e., trip price and retention fee) and quality (e.g., whether or not a trip was congested or the expected catch of red snapper or other species) attributes included in the choice experiment design. The covariates in Z_i are individual-specific observable demographics (e.g., household income or Gulf residency) and belief or preference variables from the survey (e.g., the belief that retention fees are "acceptable" or "unacceptable") that may capture heterogeneity in anglers' probabilities of opting-out of a trip that demographic data

Table 8

Alternative & Individual-specific Variables in the Extensive and Intensive Margin Models.

Variable Type	Variable	Description
X	price^{E,I}	Price of the trip
	other^{E,I}	Number of other species caught per trip
	congest^{E,I}	Vessel is "Crowded" (=1) or "Spacious" (=0)
	optout^{E}	An ASC for the outside option
Fee Version	target^{E,I}	Expected catch of red snapper on a trip
	fee^{E,I}	Fee per retained fish
Bag Limit Version	retain^{E}	The number of red snapper an angler catches and may retain
	discard^{E}	The number of red snapper an angler catches above the bag limit
Z	gom_resident^{E,I}	=1 if an angler is a Gulf of Mexico resident
	acceptable^{E,I}	=1 if the angler said retention fees are acceptable
	unacceptable^{E,I}	=1 if the angler said retention fees are unacceptable
	income^{E,I}	Annual household income (in $10,000s)
	gomfishing_years^{I}	Tens of years of experience an angler has fishing in the GOM
	Vfeetoboat^{I}	=1 if an angler was told fees would go to the headboat captains
	knew_pilot^{I}	=1 if the angler knew about the GHC pilot program at the time of his trip
	org_angler^{I}	=1 if the angler is a member of an angler organization

Note: Variables superscripted with E or I are included in the extensive or intensive margin models, respectively.

alone cannot.[38] Table 8 describes the variables included in vectors X and Z, including

[38]Past iterations of the model (not shown) also included indicators for gender, whether a respondent was told that retention fees would stay within the headboat sector or go toward research and conservation, and whether the respondent belongs to an angler organization. None of these Z_i covariates were significant in explaining trip choice and were not included in the final models.

the trip attributes that are specific to the fee or bag limit versions of the choice experiments.

I pool bag limit and retention fee choice experiment data in the above utility function, and therefore assume that price and non-catch trip attributes have the same effect in both scenario types. There is more than one way to represent the catch and retention attributes under the bag limit scenario; I have chosen to represent them in terms of retention ($retain$) and discards ($discard$) using the expected catch of red snapper and the bag limit for a given trip choice. If expected catch exceeds the bag limit, then $retain$ equals the bag limit and $discard$ equals expected catch less the bag limit. However, if the bag limit is not binding, then $retain$ equals expected catch and $discard$ equals zero.

To account for the potential of unobserved preference heterogeneity, I also estimate a panel random parameters logit in which I let parameters for the alternative-varying covariates differ across individuals (Train, 2009). I assume all random preference parameters are both uncorrelated and normally distributed, with the exception of *price*. I consider model specifications with a fixed price coefficient and a specification allowing for heterogeneous price responses by assuming β_{price} is distributed log-normally so that $-\beta_{price}$ (reported) is strictly negative. The random parameter specifications are estimated using maximum (simulated) likelihood.

I use my extensive margin models to draw population-scale conclusions and to simulate policy scenarios. I therefore use inverse probability weights in estimation. These weights account for non-response and sampling design bias and ensure my data are spatially and temporally representative of the headboat population. Appendix B.2 provides details on the calculation of these weights.

I use data from the retention fee scenarios in which individuals choose a fishing trip to estimate a censored Poisson model of the number of fish anglers retained conditional on having chosen to take a fishing trip (i.e., intensive margin demand). This Poisson regression is top-censored by the expected catch of red snapper (*target*) presented in the chosen option of the previous choice experiment, because anglers cannot retain more fish than they catch. Let y_{ijc} be the observed, top-censored retention count, and y^*_{ijc} the uncensored, latent retention count. The top censoring point (i.e., expected catch of red snapper) is U_{ijc}. If $y_{ijc} < U_{ijc}$, then $y_{ijc} = y^*_{ijc}$. This censored Poisson can thus be represented as

$$E(y^*_{ijc}|X_{ijc}, Z_i) = exp(\beta' X_{ijc} + \gamma' Z_i) = exp(\zeta_{ijc}) \tag{3.2}$$

with a weighted log likelihood of

$$\begin{aligned} LL = \sum_{i=1}^{N} \Bigg\{ w_i \Bigg[& d_{ijc} \left(-exp(\zeta_{ijc}) + y_{ijc}(\zeta_{ijc}) - ln(y_{ijc}!)\right) + \\ & (1 - d_{ijc}) ln \left(1 - \sum_{k=0}^{U_{ijc}-1} f(k|X_{ijc}, Z_i) \right) \Bigg] \Bigg\} \end{aligned} \tag{3.3}$$

where $d_{ijc} = 1$ if $y^*_{ijc} < U_{ijc}$ and w_i denotes inverse probability sampling weights.

As in the extensive margin model, X_{ijc} and Z_i are vectors of alternative-specific and individual-specific characteristics that drive retention decisions. I include several additional covariates in Z_i that may matter for retention decisions but not for trip-taking decisions in this extensive margin model. For example, I hypothesize that anglers with more years of experience fishing in the GOM have a stronger preference for red snapper retention than other, less experienced anglers (Table 8).

The probability that an observation is included in the censored Poisson estimation is the joint probability that individual i was included in the extensive margin estimation (this is captured by the extensive margin inverse probability weights discussed in section 4.5) and the predicted probability (from the extensive margin model) that individual i chose a non-opt-out option in the choice experiment question. I weight the estimation of the intensive margin model using the product of the extensive margin weights and the inverse probability that individual i selected $j \neq 3$ for each included scenario (see Appendix B.3).

The trip demand and retention demand models, when combined, provide an architecture to predict the effects of alternative policies on aggregate angler behavior, welfare, and impacts to fishery resources. Given my primary interest in this paper on the interactions between trip-level pricing vs. "a la carte" pricing for individual removals from the resource stock, I use my extensive and intensive margin models to predict trip and per-trip retention demand across a grid of policy-relevant trip prices and tag prices (or, equivalently, retention fees). I use trip-level logbook data to calibrate these predictions so that they reflect actual trips taken and red snapper harvested aboard GHC vessels in the two years prior to the pilot program (2012-2013) under a set of representative conditions and trip attributes. For a complete description of the simulation and calibration procedure, please refer to Appendix B.5.

3.6 Results

3.6.1 Modeling Results

Table 9 presents the estimation results for a conditional logit model (column 1) and two random parameters logit (RPL) model specifications (columns 2 and 3). All three models are estimated with cluster-robust standard errors which are clustered by

Table 9

Conditional Logit and Random Parameters Models of Trip Choice.

			(1) C logit	(2) RP logit fixed price	(3) RP logit ln(price)
price[39]		μ	-0.00698***	-0.01103***	-4.49913***
			(0.00108)	(0.00199)	(0.24597)
		σ			1.06657***
					(0.13825)
other		μ	0.07749***	0.11278***	0.14822***
			(0.01935)	(0.03104)	(0.04478)
		σ		0.16914***	0.16368*
				(0.04341)	(0.0638)
congest		μ	-0.81713***	-1.33397***	-1.49132***
			(0.10879)	(0.21852)	(0.28366)
		σ		1.12175***	1.14397**
				(0.27886)	(0.35745)
Opt out (all trips)		μ	-1.22352**	-2.50251*	-2.82661*
			(0.41718)	(0.97388)	(1.3825)
		σ		2.79362***	2.81591***
				(0.42085)	(0.52788)
	×gom_resident		-0.08123	-0.10628	-0.2129
			(0.35884)	(0.494)	(2.58804)
	×income		-0.00058	0.00111	0.00065
			(0.00226)	(0.00167)	(0.00361)
Bag Limit trips	×retain	μ	0.37398***	0.67008***	0.73978**
			(0.08569)	(0.15329)	(0.25241)
		σ		0.42388	0.64788
				(0.24951)	(0.39382)
	×discard	μ	0.06674*	0.07278	0.10376
			(0.03361)	(0.05346)	(0.0582)
		σ		0.22361	0.1598
				(0.14238)	(0.35309)

[39] To restrict price effects to be negative, the negative of price is included in model 3. The estimated mean and standard deviation of the negative price coefficient are in log scale. De-logged, the estimated μ and σ are 0.01964 and 0.02859, with robust standard errors of 0.0033 and 0.0069, respectively. The formulas for finding these values are: $mean = exp(\mu + \sigma^2/2)$ and $sd = \sqrt{exp(2\mu + \sigma^2)[exp(\sigma^2) - 1]}$.

Table 9

Continued from previous page

				(1) C logit	(2) RP logit fixed price	(3) RP logit ln(price)
Fee trips	×target		μ	0.04699*	0.05777	0.09356*
				(0.0222)	(0.0395)	(0.04159)
			σ		0.19928**	0.17906
					(0.07194)	(0.11073)
	×fee		μ	-0.02359***	-0.0396***	-0.04446**
				(0.00348)	(0.00791)	(0.01497)
			σ		0.01654	0.01356
					(0.01663)	(0.03694)
	×opt out			-0.28141	-0.03516	-0.04209
				(0.41082)	(0.18729)	(1.04215)
		×gom_resident		0.48189	0.83708	0.9431
				(0.35267)	(0.6266)	(1.12054)
		×income		-0.00114	-0.00192	-0.00167
				(0.00205)	(0.0027)	(0.00553)
		×unacceptable			0.13684	-0.08957
					(0.8946)	(0.58371)
		×acceptable			-2.16461*	-2.76009***
					(0.89996)	(0.67615)
Number of individuals				537	537	537
Number of choice occasions				4	4	4
Number of observations				2148	2148	2148
LL				-2053.874	-1826.447	-1778.609
Pseudo R2				0.1241	0.2167	0.2365

Cluster robust standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

individual respondent to allow for possible correlation between responses. The non-price random parameters in both RPL models are drawn from normal distributions, while β_{price} is either included as a fixed parameter (column 2) or estimated as the negative of a log-normal distribution (column 3).[40] Many of the estimated standard

[40]Past iterations of model 2 included an unmixed *price* coefficient, as well as either *ln*(*price*) or

deviations of the random parameters in models 2 and 3 are large relative to their estimated means and statistically significant, which suggests that it is important to allow for unobserved heterogeneity when modeling the trip-taking behavior of recreational anglers. I use the estimated coefficients of model 3 in my policy simulations (section 3.6.2).

The estimated coefficients for both trip-cost variables (*price*, *fee*) are negative across the conditional and random parameters logit models. The estimated standard deviation of *price* (model 3) is large relative to its mean, which suggests there is substantial heterogeneity in anglers' responses to trip price. Conversely, the estimated standard deviation for *fee* (models 2 and 3) is small relative to its mean, which indicates little heterogeneity in fee sensitivity when it comes to trip choice.

In each of the models in Table 9, I investigate whether anglers were more likely to opt out of fishing trips for which retention is governed through fees rather than bag limits. The uninteracted base covariate *optout* has a negative and significant estimated mean and an estimated standard deviation that is both significant and large relative to its mean. In other words, holding alternative-varying attributes constant, anglers tend to opt out less often than they opt in, but this response is heterogeneous between anglers. The coefficient for *optout* under "Fee Version" is small and insignificant, which suggests that anglers were no more or less likely to opt out of a trip conditional only on their red snapper retention being governed by fees rather than bag limits. Anglers who found retention fees to be acceptable were less likely than those who were either ambivalent toward (the omitted base interaction) or opposed to retention fees to opt out of a trip conditional only on it being a "fee trip." This finding suggests that there

$price^2$, neither of which were significant. Thus, I am confident that my random parameters logit models capture the true, linear relationship between price and trip-taking probability.

were behavioral consequences (at least in terms of stated preferences) of professed attitudes toward the use of retention fees.[41] Understanding the mix of these attitudes in the angler population is therefore important for understanding the overall scale of demand under this proposed policy. Nevertheless, this heterogeneity may be of limited usefulness for policy targeting since fee attitude is not a verifiable attribute on which policy can be differentiated.

If fee acceptance tends to vary along certain demographic margins (e.g., income) then I might be concerned about the distributional implications of the differential impact of retention fees on trip-taking as discussed above. In order to investigate potential distributional concerns and to identify observable, policy-relevant attributes with which fee acceptance might be correlated, I estimate an ordered logit model of fee acceptance on angler characteristics (see Table 19 in Appendix B.6) which reveals that younger, male anglers with higher annual household incomes are more likely to be accepting of retention fees. These findings suggest that uncoupled pricing could promote elitism if, as a result of being less approving of retention fees, lower income individuals are induced to take relatively fewer fishing trips. Even though income is a significant determinant of fee acceptance, I found in Table 9 that only fee acceptance and not income significantly impacted the probability of taking a fee version headboat trip.

In addition to looking at differential opt-out behavior between bag limit and fee trips, I also investigate how trip-taking depends upon on marginal changes in fee magnitude. At first impression, the coefficients in Table 9 suggest that trips hinge more on changes in the retention fee than on changes in trip price. The average

[41] Note that all respondents were asked about fee acceptance prior to their exposure to the choice experiment section of the online survey, so that it can be treated as exogenous to the level of the fee in the extensive and intensive margin models.

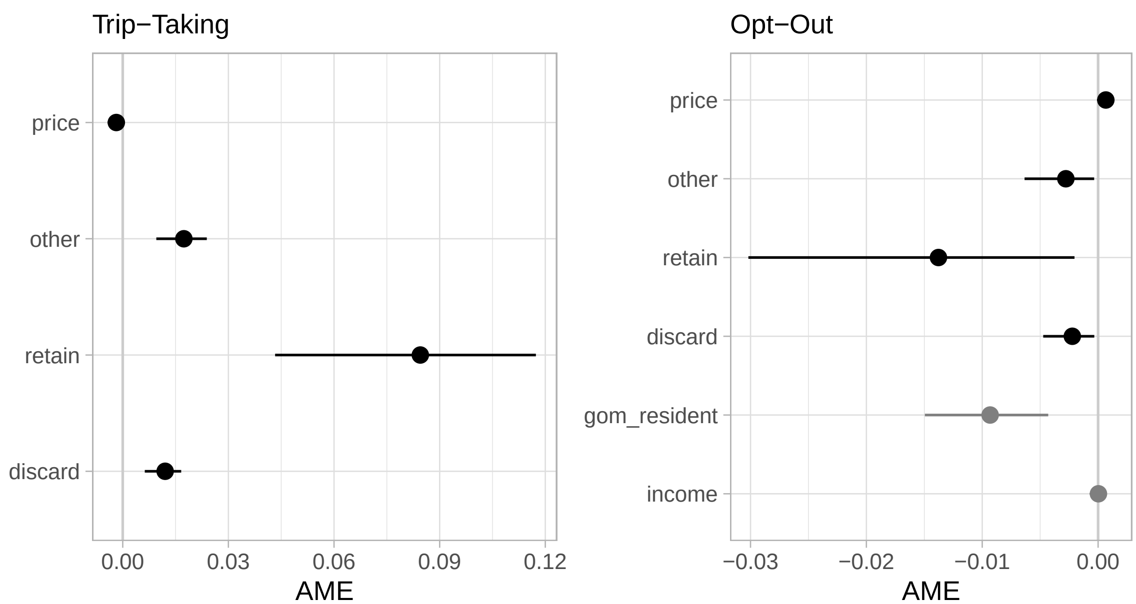

Figure 6. Mean and Coverage (5th to 95th percentiles) of Average Marginal Effects on Trip Choice and Opt-out Behavior for the Bag Limit Questions. Calculated using model 3 (Table 9).

marginal effects presented in the “trip-taking” panels of Figures 6 and 7 are the effects of a change in each trip attribute on the probability of an angler choosing alternative one, while the “opt-out” panels indicate how changes in the listed trip attributes impact the probability of a respondent choosing the outside option over one of the two listed trip alternatives. Given that my data come from an unlabeled choice experiment in which the trip alternatives are differentiated by randomized attributes, the average marginal effects should be the same for trip alternatives one and two.[42] A one dollar increase in the retention fee for trip one reduces the probability of that alternative being chosen 3.4 times more (0.0051 vs 0.0015) than does a one dollar increase in alternative one’s trip price (see Figure 7). Furthermore, respondents are willing to pay

[42] I also calculate these marginal effects for alternative two to confirm that there was no systematic difference between the two trip alternatives, and confirm that there are trivial numerical differences between the two sets of marginal effects.

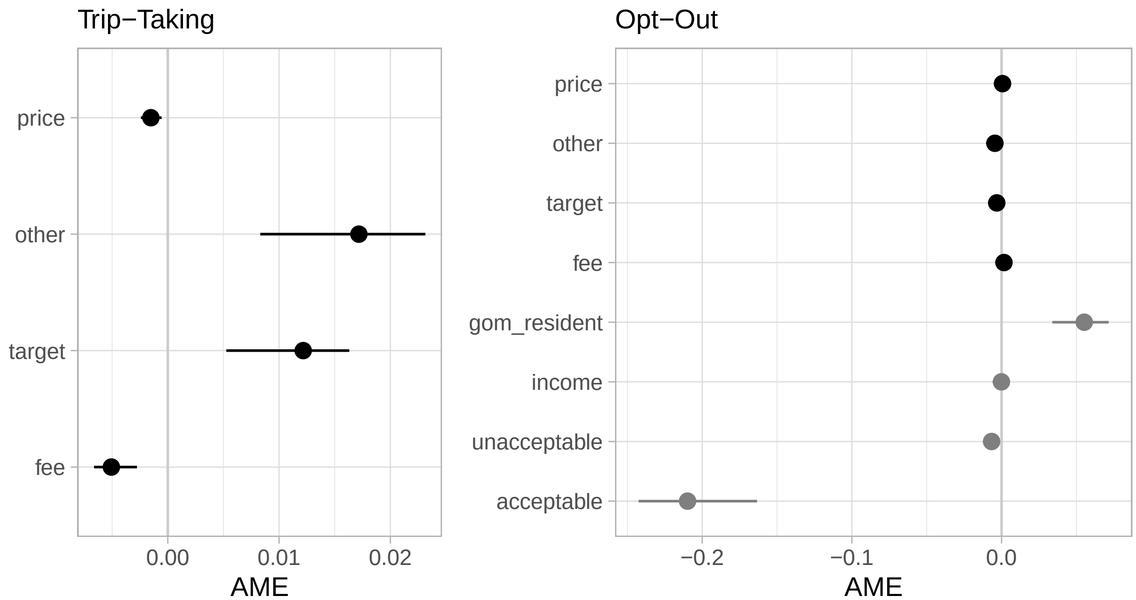

Figure 7. Mean and coverage (5th to 95th percentiles) of Average Marginal Effects on Trip Choice and Opt-out Behavior for the Fee Version Questions. Calculated using model 3 (Table 9).

an average of \$3.68 (sd =\$1.56) more in trip price to avoid a \$1 increase in retention fee.[43] Perhaps anglers are so averse to the idea of retention fees that they will accept higher trip prices to avoid higher retention fees. Alternatively, the average angler may anticipate catching and retaining approximately four red snapper on a fee-based trip, so that a \$1 increase in either retention fees or trip price is equivalent in welfare terms. The latter hypothesis suggests that anglers are agnostic about whether their dollars are spent on trip prices or retention fees.

To investigate the latter hypothesis, I estimate two additional conditional logit models of trip-choice using only fee version observations for which anglers did *not* choose the outside option. In other words, I model anglers' decision about which of

[43]All WTP estimates were calculated via bootstrapping using 1,000 draws of each of the random parameters. I used model 2 for all WTP estimates, because the estimates produced using model 3 were unrealistically large. This is because the price parameter is distributed log-normally with a near-zero mean in model 3.

Table 10

Conditional Logits of Trip Choice (Non Opt-out) Under the Fee Version.

	(1)	(2)
price	-0.00655***	-0.00677***
	(0.00183)	(0.00182)
other	0.0420	0.0294
	(0.0275)	(0.0264)
congest	-0.826***	-0.741***
	(0.192)	(0.183)
target	0.0333	0.186***
	(0.0277)	(0.0530)
fee	-0.0227***	
	(0.00502)	
fee × target		-0.00541***
		(0.00126)
N	1486	1486
LL	-386.56691	-384.10395
$Pseudo\ R^2$	0.0896	0.0954

Cluster robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the two trips to take conditional on having decided to take a "fee version" fishing trip (Table 10). The first model in Table 10 includes retention fee magnitude as a regressor (*fee*), while the second model replaces this regressor with the maximum expected fee bill for a given trip under the assumption of full retention of catch ($fee \times target$). In the first model, the fee coefficient is 3.47 times that of the price coefficient, agreeing with the pattern noted in the RPL models in Table 9. In the second model, a Wald test confirms that the coefficients for fee bill ($fee \times target$) and trip price are not statistically different ($\chi^2 = 1.11$, $p = 0.2929$). These results demonstrate that, conditional on having decided to take a trip, anglers appear to treat the maximum fee bill and trip price in an equivalent fashion, suggesting that the seemingly disproportionate effect of fees in the trip choice model is rooted in expectations of retention.

Not only are respondents more likely to choose trips that cost less in aggregate (*price*, *fee*), but Table 9 reveals that they also gravitate toward trips that promise: 1) a higher expected catch of non-red snapper fish (*other*); 2) less congestion on the vessel (*congest*); 3) higher expected catch of red snapper (*target*, fee version); and 4) more red snapper retained (*retain*, bag limit version). The estimated standard deviations for *other* and *congest* are significant and large relative to their means (models 2 and 3), which indicates a meaningful degree of heterogeneity in how anglers' trip-taking behaviors respond to changes in non-price and non-catch trip quality attributes. The average marginal effect of a trip being "crowded" (*congest*) on its probability of being chosen is -0.184 and -0.171 for bag limit and fee trips, respectively. The marginal effect of congestion is relatively large and variable, so I omit *congest* from my AME visualizations in Figures 6 and 7 to preserve meaningful scale for the other variables.[44,45] See section B.4 of the appendix for details on how I calculated AMEs.

While all three models suggest that the number of red snapper an angler expects to catch and retain is a significant and positive determinant of trip choice for bag limit trips, any fish that anglers catch and discard (i.e., red snapper caught in excess of an angler's bag limit) yield little to no marginal utility. Figures 6 and 7 show that

[44]The bars around the average marginal effect point estimates represent the range of all average marginal effect estimates across 1,000 sets of individual-specific draws for each random coefficient.

[45]The 5th percentiles, means, and 95th percentiles of AMEs for congest in Figures 6 and 7 are as follows: Trip-taking behavior, bag limit version: (-0.237,-0.184,-0.131); Opt-out behavior, bag limit version: (0.007,0.042,0.086); Trip-taking Behavior, fee version: (-0.223,-0.171,-0.103); Opt-out behavior, fee version: (0.015, 0.058, 0.102).

a one fish increase in retention on a "bag limit trip" increases the mean probability of an angler taking a particular trip by 0.085. If, however, that same angler expects to discard that additional fish, then the probability that they will take that same trip only increases by 0.012. The average marginal effect of catching an additional red snapper on a "fee trip" is also 0.012. This result is consistent with that of Carter and Liese (2012), who find that recreational anglers were willing to pay more than eight times as much to catch and retain red snapper than they were to catch and release red snapper under a bag limit. The lack of marginal utility from a discarded fish suggests that providing anglers the ability to effectively purchase a larger ex post bag limit through retention fees should be welfare improving when applied to red snapper and other GOM reef fish, particularly for more highly-skilled anglers for whom the bag limit is especially likely to bind.[46] Furthermore, if anglers with higher marginal values of retention are also more likely to be constrained by the bag limit, then a switch to retention fees could further improve allocative efficiency by inducing anglers with higher marginal values to take relatively more trips now that they can enjoy a higher measure of trip quality.

Table 11 reports the results of top-censored Poisson regression of the number of red snapper respondents claimed they would retain, where the top-censoring is determined by the number of fish they catch in the previous choice experiment, conditional on having chosen to take a fee-based trip. Anglers who found fees to be acceptable are not only less likely to opt-out of fee-governed trips, but also tend to retain about 49% more fish on those trips, subject to not being catch-censored, than do those who are ambivalent or averse to retention fees. Anglers who like the idea of retention fees

[46]This finding that discarded fish yield no marginal utility likely would not generalize to an inland freshwater fisheries with a strong catch-and-release ethic.

Table 11

Top-censored Poisson Model of Number of Fish Retained.

		(1)
congest		0.0649
		(0.101)
other		-0.00900
		(0.0189)
target		0.183***
		(0.0274)
price		-0.000108
		(0.000728)
gom_resident		-0.0355
		(0.104)
gomfishing_years (10 years)		0.0869*
		(0.0361)
income		0.000972
		(0.000741)
Vfeetoboat		0.0902
		(0.101)
unacceptable		-0.106
		(0.250)
acceptable		0.401**
		(0.182)
fee		-0.0231***
		(0.00589)
	× unacceptable	0.00308
		(0.00766)
	× acceptable	0.00125
		(0.00704)
_cons		0.348
		(0.277)
N		736
LL		-643.79706

Cluster robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

may have overstated the number of fish they would retain if they believed that such a response could increase the probability of such a policy being adopted. However, it is also possible that anglers who approved of retention fees did so because they have a stronger baseline preference for retention than do other respondents. I cannot, with my data, determine to what degree strategic behavior may have played a role in this result, but the acceptability indicators clearly capture some latent difference in anglers who approved of or were ambivalent or opposed to retention fees.

The fee coefficient in Table 11 is negative and significant, suggesting each \$1 increase in fee reduces retention by 2.3%.[47] However, neither of the interactions between fee and fee acceptance are significant, suggesting that, while fee acceptance can act as a retention shifter, it is not a significant determinant of fee elasticity.

Figure 8 shows that anglers exhibit inelastic retention behavior at low fee levels (\$10 per fish) but behave in a more fee-elastic manner when faced with high retention fees (\$50 per fish). Above \$56, demand becomes elastic, so that further increases in the retention fee will induce relatively larger reductions in retention on a given trip. However, this result does not provide the "switchpoint" fee level for overall demand, since fee magnitude impacts both extensive and intensive margin behavior. For this I must combine the two demand functions (see below).

Interestingly, the trip quality attributes that are not related to target species retention (i.e., *congest*, *other*, and *price*) are all insignificant in the trip retention demand equation. This suggests that anglers treat the utility maximization decision from retention under fees in a separable manner from these predetermined trip attributes. Demographic characteristics such as income or Gulf residency also do not

[47]A past version of the censored Poisson (not shown) included a fee^2 term, which was found to be insignificant.

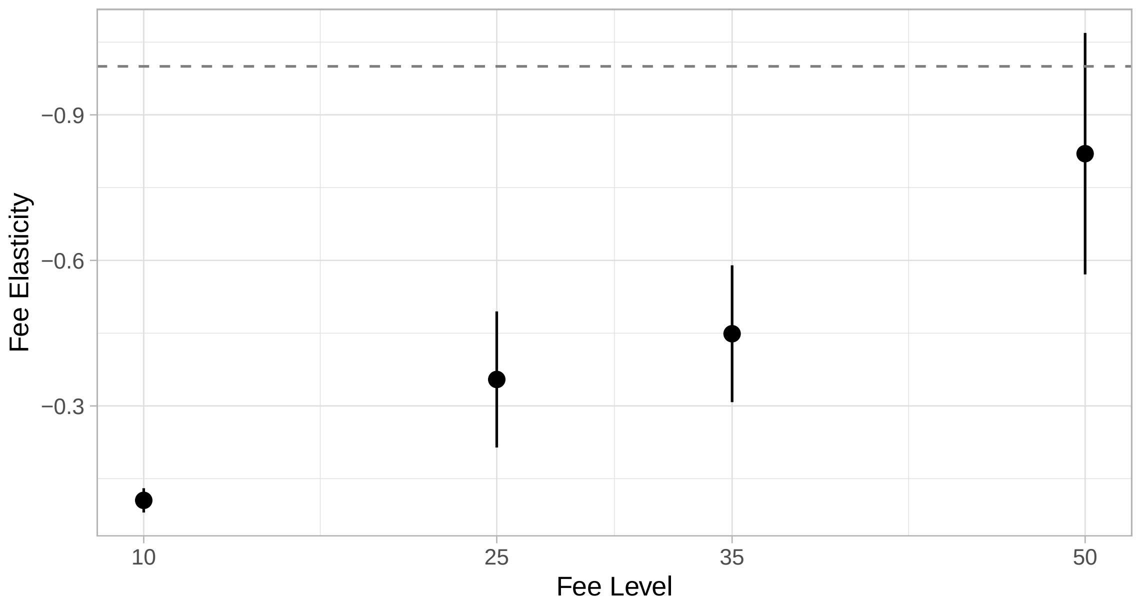

Figure 8. Fee Elasticity at the Four Randomized Fee Levels with 95% Error Bars.

explain fish retention behavior, and other specifications (not shown) revealed that gender, employment status, and whether or not a fisherman was a member of an angler organization are similarly insignificant.

The only demographic characteristic that influences per-trip retention demand is how many years of fishing experience the angler has in the GOM. On average, an additional 10 years of experience fishing in the Gulf translates to an 8.69% increase in fish retention. While GOM residents tend to have more years of experience fishing in the Gulf than non-residents (two-sample t test, p = 0.0000), angling experience, not residency, is the relevant mechanism of the two for predicting retention behavior.

Target, or the number of red snapper that an angler expects to catch on a trip, is a trip-attribute that is both a regressor and a censoring point for this regression. I include *target* as a regressor because the number of red snapper that anglers expect to catch may influence the number they decide to retain even if their desired retention is not censored by catch. In other words, target retention may increase as catch goes up, even if catch was not “binding” on the retention decision (i.e., some catch was previously discarded). This could occur due to heuristic decision making (e.g., retaining a fixed proportion of catch) or due to an angler having a distaste for discards that leads them to increase their retention as their luck in catching fish improves. Indeed, I find that a one fish increase in target catch increases uncensored retention by approximately 18% (Table 11). However, I find that the estimates of all coefficients, save for *congest* and *other*, are insensitive to the inclusion or exclusion of *target* as a regressor.

3.6.2 Policy Simulations

In my policy simulations, I assume GOM headboats remain a limited access sector whose trip prices are determined in a market, and I interpret retention fees as the cost of a harvest tag. For the sake of simplicity, I assume that these tags are uniquely allocated to harvest in the GHC subset of the headboat sector and not usable outside of it, thereby ignoring any spillovers between the private, non-GHC headboat, and for-hire recreational sectors or between recreation and commercial fishing. These tags must be traded in a competitive market, either through brokers (including, potentially, headboats themselves) and/or through resale markets.

The way I interpret my policy simulations is just one of multiple ways in which pricing for fish retention could be implemented. Another possibility that works in the specific case of for-hire vessels such as headboats is to allocate vessels proportional rights to a share of the annual total allowable catch in the fishery, as in an ITQ. This is exactly what happened during the GHC pilot, although allocation technically occurred to to the GHC as a cooperative, with vessel-level allocation resolved by GHC members (Abbott & Willard, 2017). Vessels are then free to allocate their scarce fish quota to customers in whatever way they like, including implementing retention pricing. In this case retention pricing would be similar to a leasing arrangement in commercial ITQ fisheries, where vessel owners “lease” quota to customers according to their desire to retain fish, in addition to charging for the trip itself. If annual allocation is freely transferable across vessels, then the resulting market clearing price (and the price charged to customers) should equal the marginal WTP of customers for retention of an additional fish. Note, however, that an ITQ or cooperative allocation to headboats may not be sufficient to guarantee such “a la carte” pricing, as vessels may elect to utilize other approaches to rationing their allocation – including creation of differentiated trips with higher bag limits and attendantly higher prices – either out of concern for alienating customers or due to the transaction costs of implementing individualized retention pricing on individual trips (Abbott & Willard, 2017).

While most consistent with the GHC policy experiment, this ITQ/cooperative approach has limited applicability beyond for-hire recreational providers. Allocation of a finite number of durable share rights to harvest is would likely be problematic for recreational fishing where participation and catch history are often lacking and, even if present, the allocation of shares to thousands of claimants may be infeasible and not worth the administrative costs. Furthermore, unless quota are auctioned annually or subject to some form of royalty tax, “quota rents” would go to the for-hire headboat sector. Resource managers may instead wish to receive supplemental “a la carte” pricing revenues on top of the permit fees already collected from headboat operators.

An alternative, more generally applicable, approach is to consider the distribution of a finite number of harvest tags per season which must be surrendered for every unit of recreational harvest. These tags may be physical, virtual, or a mix of the two, and can be allocated in a number of ways, each with different distributional, efficiency, and revenue-raising implications. For example, tags could be auctioned off directly to anglers or to brokers such as sporting goods stores who then provide a ready spot market for anglers – either of which provides a source of revenue for resource management. In other cases where equity concerns dominate, particularly when tags are scarce (as for trophy species), tags may be allocated, at least partially, by lottery. To maximize efficiency within this tag market, R. J. Johnston et al. (2007) suggest allowing tag resale.

Tags are not without their challenges, including the challenges of enforcement and the problem of accounting for discard mortality, both of which are common challenges of fisheries management and not endemic to harvest tags alone (Abbott, 2015; R. J. Johnston et al., 2007). Nevertheless, their widespread use in game management and for some freshwater fisheries suggests they could be more widely adopted in marine contexts. Indeed, bag limits already impose quantitative limits on individual anglers' harvest, so the marginal enforcement costs of a tag program may not be much higher. Finally, unlike recreational ITQs, tags have the potential to work across both the for-hire sector and for anglers fishing from their own private boats. In spite of these challenges and for the reasons discussed above, I believe that representing my simulations in terms of market-based trip prices on the extensive margin and harvest tags on the intensive margin makes sense in this context.

Figure 9 illustrates how different combinations of trip and tag prices affect both predicted harvest of (represented by white curves) and tag-based revenues (captured by the gray contours) generated by GHC clients. Not surprisingly, tag revenues and total harvest fall as trip prices increase for a given tag price. Nevertheless, predicted

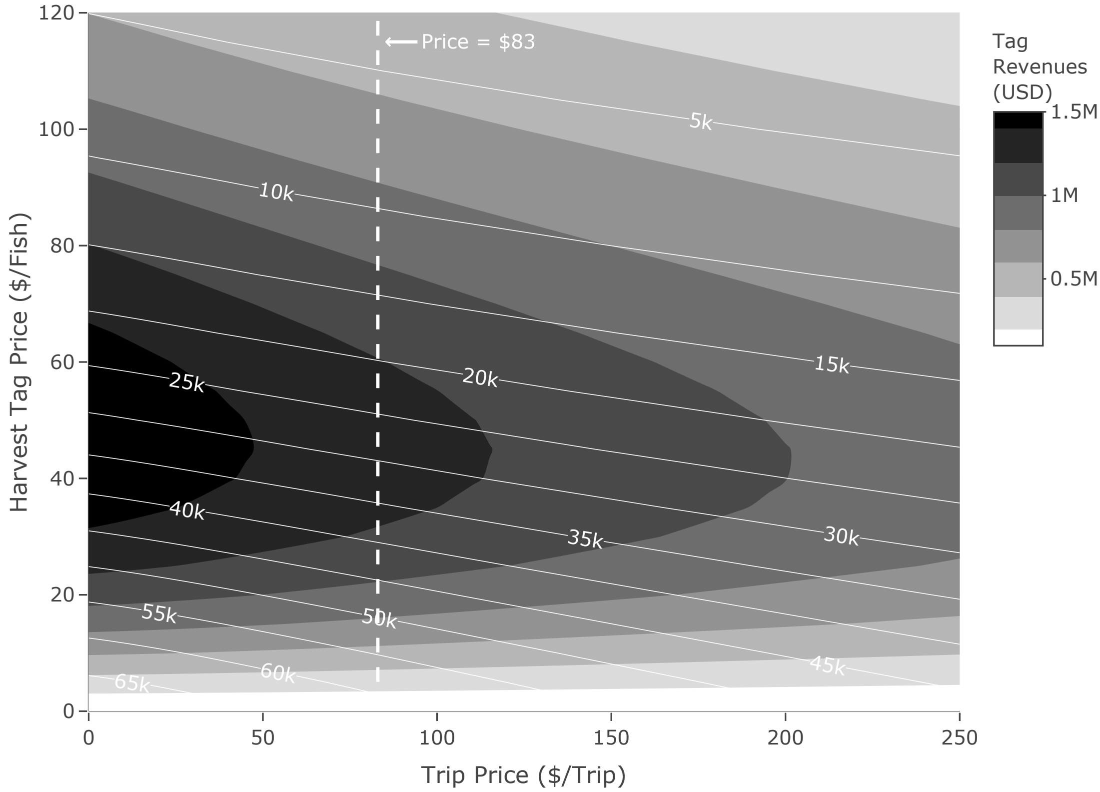

Figure 9. Harvest Tags Demanded (white lines) and Revenues Generated from Tag Sales (gray bars) at Different Bundles of Trip Prices and Harvest Tag Prices.

trips are inelastic to trip prices, so that harvest is relatively unresponsive to even large pricing changes on the extensive margin. Incentives on the intensive margin, therefore, are especially valuable. The backward-bending revenue contours demonstrate that there is a range of low tag prices where retention is inelastic, but that eventually a breakpoint is reached where retention responds disproportionately to further increases, leading to reduced revenues. This breakpoint tag price declines, albeit slowly, as trip prices increase. The relatively close vertical spacing of the harvest contours, particularly at lower tag prices shows the sensitivity of harvests to pricing changes on the intensive margin. Of course, in practice resource managers have no direct control of the trip pricing itself as this will depend on market-clearing outcomes in the

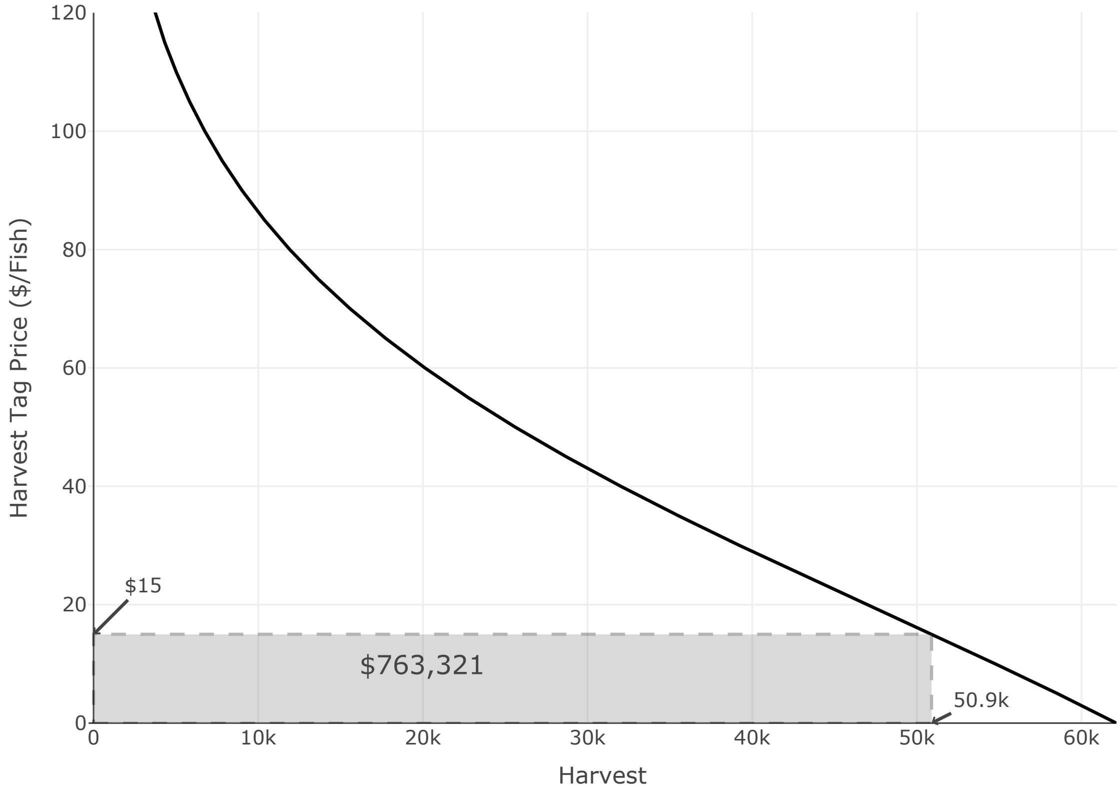

Figure 10. Demand Curve for Red Snapper Harvest Tags and Revenue from Tag Sales (gray box) when the Price of a Headboat Trip is $83.

headboat sector, which is outside the scope of my model and data. Nevertheless, these economically grounded simulations can help managers anticipate how pricing shifts from demand shifts (aside from the fish stock itself) or supply shocks (e.g., hurricane damage to the headboat fleet) may influence harvest or tag market outcomes. Indeed, if a finite number of harvest tags (say 50,000) are allocated for a season, then the harvest contour associated with this quantity represents the locus of trip prices and tag prices that support equilibrium in the tag market.

Figure 10 is the simulated Marshallian demand curve for red snapper harvest tags by anglers on GHC vessels when the market price of a headboat trip is $83—the median price of a headboat trip aboard GHC vessels in 2012-2013—under the distribution of catch rates (and hence abundance) in those years. It reflects *overall* demand for red snapper as harvest tag prices (or retention fees) vary, accounting for both trip decisions and retention decisions by anglers. Demand for harvest tags is inelastic below prices of \$45 per tag, and becomes elastic above that level. In 2012-2013, anglers aboard the 19 GHC vessels harvested approximately 50,000 red snapper per year. Therefore, if just over 50,000 harvest tags were allocated to anglers fishing on GHC vessels and trip price remained at \$83, then the market-clearing price for a harvest tag would be \$15, generating \$763,321 in tag revenues from this subset of the recreational headboat sector alone (excluding other recreational anglers), which could accrue either to fisheries management or brokers depending on the means of allocation. For context, the commercial red snapper IFQ program collects a 3% ex vessel tax on revenues in order to recover the incremental management costs of the program, and in 2020, \$950,396 of cost recovery taxes were collected (National Marine Fisheries Service Southeast Regional Office, 2021). The commercial sector has historically received 51% of the annual red snapper quota, while the for-hire sector, which is partially-comprised of Gulf of Mexico headboats, receives only 20.73% of the red snapper quota each year (National Oceanic and Atmospheric Administration, 2021). My policy simulations are scaled to represent the sub-segment of the headboat for-hire sector that participated in the GHC. Thus, my estimate of \$763,321 in tag sale revenues is not insignificant.

An allocation of 27,000 harvest tags, on the other hand, would maximize tag revenues (\$1.22 million) under 2012-2013 harvest conditions and result in a market price for a tag of \$45. However, this finding assumes that there is no feedback between tag scarcity and the pricing of headboat trips, which is less likely as tag prices rise.

Figure 10 is also of interest for informing often contentious discussions about allocation of harvest between sectors (Abbott, 2015). Previous allocation studies have used estimates from recreation demand models to estimate the marginal value of increasing allocation to the recreational sector vs. the commercial sector. One challenge of these studies is that they are predicated on the existing regulatory structure and therefore must come up with some story for how "new" fish would be allocated to anglers (i.e. through increasing bag limits on existing trips, new trips under existing bag limits, etc.), where this "rationing" approach must be linked to the manner in which recreational values are recovered. For example, in their study of red snapper allocation in the GOM, Agar and Carter (2014) find that anglers in the broader recreational sector would be willing to pay the equivalent of \$71 a fish (or \$11.21/lb.) for moving from zero to 2 fish bag limits for red snapper. These values are then compared to lease prices in the commercial ITQ market to argue that reallocation of harvest to recreational harvesters is consistent with allocation according to the equimarginal principle. However, these estimates are predicated on the existing, inefficient allocation of fish under the regulated open access, season-length/bag limit regulatory approach, which does not allocate harvest according to diminishing marginal valuation (Holzer & McConnell, 2014). Therefore, these values do not answer the question of whether existing allocations to the sectors are efficient if allocation *within* the recreational sector were allocated efficiently, as in a tradable tag market. However, my estimates—by being predicated on price-based allocation among headboat passengers—do allow for this comparison

I find that a hypothetical harvest tag market among GHC anglers in 2012-2013 would have cleared at a price of approximately \$15 a fish. Given a mean weight of 6.3 pounds per fish (Agar & Carter, 2014), this implies a price of \$2.38/lb in the headboat sector. However, the lease price of allocation in the GOM red snapper fisher—a value of the marginal profitability of an additional pound of allocation to commercial fishers—was approaching \$3 in approximately the same time period (Gulf of Mexico Fishery Management Council, 2013). Therefore, the efficiency case for reallocation to recreational anglers (or at least those in the headboat sector) is hardly as clear-cut as the previous analysis might suggest. Opening up trade in allocation between commercial fishers and the headboat sector may not lead to reallocation away from commercial fishing, particularly if quota is efficiently allocated *within* the headboat sector itself. Indeed, the high valuation reported by Agar and Carter for additional red snapper may exist for the very reason that bag limits and season constraints are currently misallocating fish to many anglers with low valuations, so that the *marginal* value of loosening the allocation constraint is artificially high (Holzer & McConnell, 2014). my model shows how the outcomes of market-based allocation between sectors can be addressed by explicitly modeling the allocation of recreational harvest via market mechanisms.

3.7 Conclusion

My policy simulations show that "a la carte" pricing has the potential to address multiple management goals within the US GOM recreational red snapper fishery, including: meeting biological objectives, generating efficiency gains, and providing supplemental revenue for resource managers. The exact form that "a la carte" management may take will depend on the unique political climate of individual fisheries. The general approach laid out in this paper can aid policymakers in determining how successful or unsuccessful a policy counterfactual may be in their respective fishery based on the representative anglers' relative responsiveness to trip prices, retention prices, and non-price trip attributes on both the extensive and intensive margins of harvest.

The combination of stated preference data and structural modeling is a powerful tool for ex ante analysis of unbundled pricing in recreational contexts, especially because I find that the impact of price and non-price trip attributes on trip-taking and retention behavior is subject to unobserved heterogeneity. Specifically, anglers' views about the acceptability of pricing the resource influence opt-out behavior and per-trip red snapper retention on fee version trips. This behavior-shifting heterogeneity is unobserved so it cannot be targeted with policy. It is therefore important to utilize structural modeling that accounts for unobserved heterogeneity in order to understand how a body of anglers might adapt their trip-taking or retention behavior in aggregate in response to any policy instruments under consideration.

The modeling approach in this paper could be used to investigate policy contexts beyond the intra-sectoral allocation of harvest tags to brokers and headboat anglers. In this paper, my policy modeling is restricted to include retention demand only from the recreational headboat sector; I do not model a unified tag market for the private and for-hire recreational sectors, because I do not have information on private angling demand, and therefore do not know how this unified market would equilibrate. However, it seems likely that establishing a single harvest tag market across recreational sectors would enable inter-sector allocation to resolve itself through the tag market. Furthermore, by accounting for the impacts of pricing the resource on both the trip-taking and retention margins, I find evidence that allocating tradable short-term rights that are transferable between recreational anglers (or at least passengers of headboat vessels) and commercial harvesters may result in quota flowing toward the commercial sector, in contrast to the current narrative that recreational anglers have higher marginal values for harvest.

My findings are not directly applicable for intensive resource use that is not extractive (e.g., trail degradation from hiking, mountain biking, or ATV use) because the information and enforcement costs associated with pricing non-extractive use are likely prohibitively high. However, unbundled pricing could yield similar benefits to resource managers whose resources are subject to extractive uses on the intensive margin, and the data collection, and modeling approaches illustrated in this paper could provide insight on how differentiated pricing mechanisms may actually play out in their specific contexts. For instance, harvest tags are already common in hunting, and especially for trophy species. This type of model may aid game managers in allocating the correct number of tags to meet their objectives, as well as to anticipate how the market clearing price for tags may change in response to changes in demand (suppose the population of a substitute species surges, leading to decreased demand for the target species) or in supply (say, through climate shocks or fire.)

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Chapter 4

MONEY CAN'T BUY ME FISH: LESSONS FROM AN INCENTIVIZED HARVEST PROGRAM

4.1 Introduction

Federal and state or regional wildlife management agencies must balance multiple, often competing objectives, including: protecting endangered species, identifying and controlling for invasive species, and more. The systems these agencies manage are increasingly characterized by significant recreational use. In the United States alone, more than 97% of people aged 16 years and older recreate out-of-doors in any given year (Interagency National Survey Consortium, n.d.). The prevalence of outdoor recreators in these human-environment systems makes managing species populations both more important and more complex; healthy, biodiverse ecosystems improve the quality of recreational opportunities, but the spillovers of recreation may hinder management efforts. As the type and scale of anthropogenic impacts on resource systems continue to evolve, resource managers will need to adapt their portfolio of tools to address increased species migrations and other external shocks to their systems.

Broadly speaking, resource managers have two tools at their disposal—quantity instruments and price instruments. For example, a manager seeking to protect or maintain a population of recreationally-desirable fish or game might limit individual take through bag limits (a quantity instrument) or require fishers and hunters to buy a harvest tag (a pricing instrument) for each fish harvested. Conversely, managers whose objective is population control may cull a pre-determined quantity of an invasive species or offer a bounty to incentivize its recreational harvest.

In this paper, I investigate the potential for the price instrument "harvest incentives" to meet multiple management objectives using the case of an incentivized harvest program for invasive brown trout in the Lees Ferry recreational fishery. Harvest incentives are an increasingly popular tool of resource managers for controlling populations of invasive species. These programs augment recreational hunters' and anglers' pre-existing incentives to hunt and fish by providing a cash reward for harvesting a member of a target species. Bounties on invasive species belong to a broader family of price-based tools designed to subsidize "green" behaviors, such as water efficiency (Scheierling et al., 2006), energy efficiency (Allcott et al., 2015; Nauleau et al., 2015), purchasing electric vehicles (Li et al., 2018; Sheldon & Dua, 2019), etc. As such, bounties suffer from a similar policy challenge: uncertainty in the quantity of environmentally-beneficial behavior induced by the program (Weitzman, 1974).

When managers implement a price-based incentive program, they rarely have sufficient knowledge of the private benefits and costs of the population they are seeking to incentivize to reliably predict the impact of the subsidy (e.g., the number of additional fish harvested). Therefore, while price-based incentives may do a good job of incentivizing pro-environmental behavior by those who can do so at lowest cost, they nonetheless may fall short of or overshoot the level desired by managers (Weitzman, 1974). Furthermore, when a subsidy is offered for a particular observable outcome (e.g., harvesting a fish, or installing a low-flow toilet), it is possible that the cost-effectiveness of a program can be undermined by issuing subsidy payments to people who would have engaged in the pro-environment behavior without the additional motivation of the subsidy. In order to be effective as a control measure, environmental subsidy programs must induce additional environmentally-beneficial behavior rather than paying participants for behaviors in which they would already have engaged. Accordingly, researchers evaluating the efficacy of such subsidy programs have long recognized the importance of measuring program success against a valid counterfactual (e.g., Bennear et al., 2013; Brelsford and Abbott, 2021). In the case of harvest incentive programs, this means that a successful program must induce recreational fishers or hunters to harvest significantly more individuals of the target population than they would have absent the program. Harvest incentives have the potential to be cost effective relative to alternative management tools if they succeed at stimulating this additional harvest at relatively low cost.

We find evidence that the Lees Ferry pilot program, whose goal was to induce the removal of an additional 2,500 brown trout per year, failed to achieve its stated objectives. In the program's first year, the National Park Service (NPS) paid $41,529 in rewards for the 663 brown trout that were turned in for payment, of which only 13% (88) were additional. Therefore, the average reward payment per additional brown trout was $472, which is 146% greater than the anticipated $192 per-fish cost of electrofishing. The program failed to increase fishing trips taken to this remote, expensive-to-access fishery. Furthermore, it appears the program caused a compositional shift in the Lees Ferry angler base toward anglers who are more willing to retain a brown trout than the fishery's catch-and-release loving historical base, but who are also relatively less effective at catching Lees Ferry trout.

Incentivized harvest programs may be structured in a variety of ways. Some programs offer a simple monetary reward for each member of the target population harvested while others utilize more complex bundles of incentives. For example, Colorado Parks and Wildlife and the Colorado Conservation board pay anglers a flat reward of \$20 per fish to retain Northern pike caught in the Green Mountain Reservoir (Porras, 2016)), while the Pacific States Marine Fisheries Commission's Northern Pikeminnow Sport Reward Fishery program employs a more complex increasing tier price structure with a lottery-type bonus. In 2022, participants of the sport reward fishery received \$6 per-fish for their first 25 fish submitted, \$8 each for fish 26 through 200, and \$10 for each subsequent fish with a chance to catch "golden ticket" tagged fish worth \$500 each. Harvest incentive programs commonly include education campaigns (e.g., the Coastwide Nutria Control Program in Louisiana pairs an education and outreach program that focuses on the environmental benefits of nutria control with a per-tail bounty), and some—like the annual 10-day Florida Python Challenge—are supplemented by or executed as a derby or tournament event.

Harvest incentives are primarily implemented to increase the probability of the target species being pursued, and therefore controlled, by increasing the number of individuals participating in environmental management (Hassall & Associates P/L, 1998). However, there are additional purported benefits or management outcomes associated with these programs that make them appealing to fish and wildlife managers. Employing a diffuse, knowledgeable group of local hunters or anglers to remove a species with which they are familiar has the potential to provide meaningful and cost-effective supplementary effort for management agencies with limited resources, personnel, and time (Pasko & Goldberg, 2014). Furthermore, these programs have the potential to: increase public awareness of a particular invasive species problem; subsidize pest control efforts in highly-impacted areas; or be more politically-palatable than large-scale, contracted killing of members of the target population (Hassall & Associates P/L, 1998; Runge et al., 2018; U.S. Department of the Interior. Invasive Species Advisory Committee, 2014). Finally, these programs have the potential to encourage potential harvesters to hone their efficacy by researching how to target the invasive species, developing new technologies, or learning by doing.

While incentivized harvest programs are a promising tool for meeting several management objectives, they are not always effective at controlling their target populations. Examples of successful programs include the Northern Pikeminnow Sport Reward fishery program, which helped decrease predation on juvenile salmonids from 1990-2013 by 35% (Storch et al., 2014), and Louisiana's Nutria Control Program, which successfully increased nutria harvest and would likely have met its stated harvest goals with only a modest, $1 per-tail increase to the bounty (Dedah et al., 2010). Florida's Python Challenge and Utah's coyote bounty programs, on the other hand, have been less successful. Python challenge participants, when faced with the difficulty of actually locating pythons, grew less convinced that pythons were a significant management concern (Harvey et al., 2016), while potential coyote bounty hunters were largely unmotivated by monetary incentives, and the resilient coyote population quickly replaced any individuals that were actually removed (Bartel & Brunson, 2003).

It is possible that under-performing incentivized harvest programs could be redesigned to increase their efficacy. However, aside from a handful of studies evaluating individual programs' performances, there have been few efforts to synthesize lessons from existing programs in order to develop program design guidelines. Furthermore, few, if any, empirical studies of harvest incentive effectiveness explicitly incorporate a "no-program" counterfactual in their analysis, which means they are unable to determine how much reported program harvest is actually additional. My evaluation of the Lees Ferry program is unique because rather than assume 100% additionality I employ a counterfactual analysis to estimate true program-induced landings.

The dearth of empirical studies involving counterfactual analysis on harvest incentive programs is likely driven by a lack of sufficient data. Investigating the impact of program design elements on additional harvest requires, at minimum, data on recreational harvest before and after program implementation. Ideally, this type of analysis would incorporate data from an untreated counterfactual system whose recreational harvest mirrors the target system's in trends (thought not necessarily levels) in order to compare post-program harvest to what harvest would have been absent the program. The Arizona Game and Fish Department (AZGFD) has been running its Lees Ferry creel survey, which involves intercepting and surveying anglers on their fishing behaviors year-round and according to a consistent set of well-documented sampling protocols, for over a decade. I capitalize on the level of detail captured by the Lees Ferry creel to perform a novel decomposition analysis that is able to say more about how program design translates to success (i.e., additional harvest) than a traditional program evaluation approach. I separately estimate the effect of the brown trout harvest incentive on three behavioral margins which multiplicatively comprise harvest—the number of fishing trips that recreational anglers take to Lees Ferry, the number of brown trout that those anglers catch per trip, and the share of these fish that anglers choose to retain. A harvest incentive may be effective or ineffective at activating different margins, which could help or hinder program performance. These margins are also subject to different, program-independent forces that could bias my estimate of additional brown trout harvest; a decomposition approach allows me to generate more rigorous, margin-specific counterfactuals than I could for a model that estimates aggregate harvest.

Failure to account for the full range of population dynamics within a fishery may result in non-target species (in this case, rainbow trout) experiencing negative spillover effects from harvest incentive programs (Pasko & Goldberg, 2014; Paul et al., 2003; U.S. Department of the Interior. Invasive Species Advisory Committee, 2014). Therefore, I also investigate whether the program had an unintended, indirect effect on rainbow trout landings.

In the next section, I give background information on the Lees Ferry Brown Trout Incentivized Harvest Program. Then, in section 4.3, I present a conceptual model of a Lees Ferry recreational angler to illustrate how (i.e., on which margins) the harvest incentive may induce additional brown trout removals relative to an untreated baseline. In section 4.4, I describe the several sources of behavioral, biological, hydrological, and climatological data that I knit together to perform this program evaluation. The fifth section describes the methods that I use to estimate additional, program-induced brown trout harvest in the face of an unprecedented global pandemic. Finally, in sections 4.6 and 4.7 I present and discuss the results of my program evaluation.

4.2 Lees Ferry Brown Trout Incentivized Harvest Program

Lees Ferry in Marble Canyon, AZ, is an extremely remote, destination trout fishery. Because this fishery is in the tailwaters of Glen Canyon Dam, its water temperature is determined by reservoir levels above the dam in Lake Powell. When Glen Canyon Dam was constructed, the cold water released from the dam was ideal for rainbow trout, which the Arizona Game and Fish Department (AZGFD) and National Park Service (NPS) stocked accordingly (Runge et al., 2018). Since then, this stretch of the Colorado River has been managed as a trophy rainbow trout fishery. However, brown trout—which were stocked downstream in Grand Canyon National Park in the

1920s and 1930s and have since moved up-river—have been present in the fishery as a migrant stock for years.

As water levels in Lake Powell declined in response to the 2020-2022 North American Drought, water temperatures flowing into Lees Ferry from Glen Canyon Dam reached all-time highs. Brown trout, which are more resilient to warmer water temperatures and higher levels of turbidity than rainbow trout, may be better-suited to survival and reproduction in Lees Ferry than rainbow trout going forward. In 2014, brown trout established a breeding stock in Lees Ferry, and from 2014-2018, Runge et al. (2018) estimate that the Lees Ferry adult brown trout population had surged to an estimated 5,800 adults, and has a 64% chance of increasing 3-10 fold by 2038.

Brown trout are extremely piscivorous, so the increasing reproductive success and a growing size-structure of Lees Ferry brown trout incited concerns amidst fishery managers that the highly adaptive predators may not only endanger Lees Ferry rainbow trout, but that they may also migrate downstream to the confluence of the Little Colorado River—home to a native population of humpback chub (Runge et al., 2018). The stretch of the Colorado River that houses both Lees Ferry and the Little Colorado River Confluence is under the jurisdiction of NPS, who—as a federal agency—is obligated to protect humpback chub and other Endangered Species Act (ESA)-listed species.[48]

Brown trout have traditionally been managed in this stretch of the Colorado River with ad hoc electro-fishing. However, this form of mechanical removal is expensive and unpopular with local anglers and stakeholders. Runge et al. (2018) estimate that

[48]The humpback chub at the Little Colorado River confluence was, until recently, listed as an endangered species. Thanks to the Upper Colorado River Endangered Fish Recovery Program, humpback chub was reclassified as threatened in November 2021 (Endangered and threatened wildlife and plants; Reclassification of the humpback chub from endangered to threatened with a section 4(d) rule, 2021).

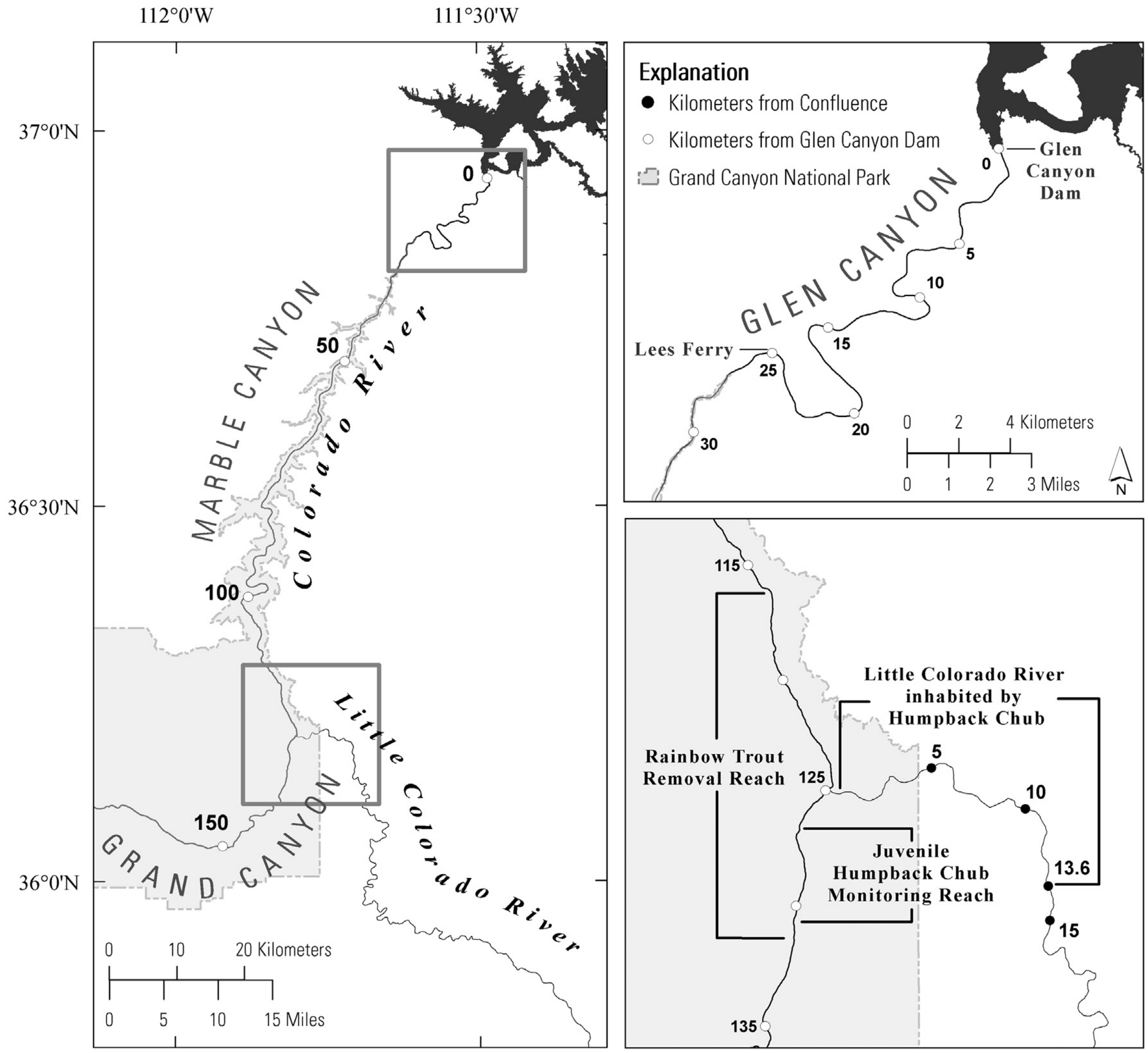

Figure 11. Study Area ("Study area", 2018).

the electrofishing effort required to control Lees Ferry brown trout would cost around $480,000 per-year, which—over a 20-year planning horizon at a 3.375% discount rate—results in a net present cost of $6.9 million. The dual appeal of a bounty program at Lees Ferry is its potential to be better-received than top-down control by the local angling community and tribes at a lower cost to GCDAMP than electro-fishing. If, at the end of its three-year pilot period, the program has failed to sufficiently increase brown trout harvest within Lees Ferry, fishery managers will resume electro-fishing on an as-needed basis to control the Lees Ferry brown trout population.

The brown trout incentivized harvest program at Lees Ferry ("the program"), initially paid anglers $25/fish to retain any brown trout caught within the Lees Ferry fishery that was at least 6 inches long. On March 1, 2021, the program reward rose to $33/fish, and as of September 1, 2021, includes a $50 bonus for every third fish turned in within the month and an additional $300 reward for any brown trout containing a scientific pit or sonic tag. This additional pit tag reward was inspired by the Northern Pikeminnow Sport Reward Fishery's "Golden Ticket" fish and was implemented to meet two objectives. First, NPS hopes that the prospect of a large payout might entice anglers to invest more effort into catching brown trout. Tag bonuses are akin to a lottery, because there is a small probability of catching a tagged fish and receiving a large payout. Kahneman and Tversky (1979) show that individuals may overweight these low probability, high payout outcomes, which could make tag bonuses a relatively cost-effective lever for increasing program participation. The second reason for these tag bonuses is that citizen science tag collection supplements ongoing monitoring efforts and could potentially improve abundance estimates.

4.3 Conceptual Model of Harvest Incentive Effectiveness

Potential Lees Ferry anglers face a certain number of choice occasions per-year in which they can decide either to take a Lees Ferry fishing trip or to do something else. Conditional on choosing to take the trip, anglers can choose how long to fish, where to fish, and what gear to use—all of which impact the number of rainbow or brown trout that they catch on that trip. Finally, the angler chooses the percent of rainbow and

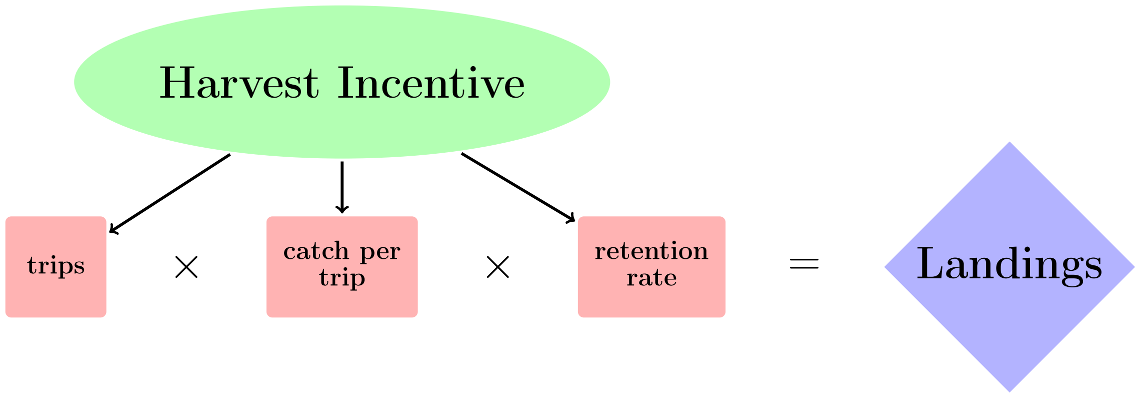

Figure 12. The Margins Along Which a Harvest Incentive May Increase Brown Trout Landings.

brown trout caught to retain rather than throwing back. The product of these three decision margins—trips-taken, catch per trip, and retention rate—is the total number of rainbow or brown trout that an angler lands or harvests in a year (see Figure 12). Rather than estimating total additional landings from the program, I separately estimate additional trips taken, fish caught per trip, and share of caught fish that were retained as a result of the program. My disaggregated approach is an improvement upon traditional program evaluations, because recreational hunters and fishers may respond more, less, or not at all on one margin or another depending upon the unique social-ecological context of a particular incentivized harvest program. For instance, a bounty for a species that is expensive to access may fail to increase trip-taking, but may induce additional catch and retention of the target species amongst those non-additional trips. Because landings are the product of these three margins, it is important to understand when and why a harvest incentive may succeed or fail at activating each margin when designing an incentivized harvest program.

The Lees Ferry program may have caused additional brown trout landings in the following ways. First, the prospect of being paid to retain a brown trout may increase the number of fishing trips that anglers take to Lees Ferry, both *extensively* by bringing new anglers into the fishery, and *intensively* by increasing the number of trips taken by existing anglers. Lees Ferry is extremely remote—the only place in over 1,000 kilometers where it is possible to drive up to the Colorado River—and expensive to access for all but a few local anglers. Individuals can access the fishery either at the Paria Beach walk-in point or via boat. In 2019, the share of boat trips that were guided vs on private, unguided vessels was about 50%. The costs of hiring a guide service or towing a private boat to a fishery as remote as Lees Ferry are necessarily high. In their review of harvest incentives, Pasko and Goldberg (2014) conclude that programs at remote, expensive-to-access sites like Lees Ferry are less likely to be successful. Therefore, the Lees Ferry harvest incentive is most likely to draw in additional trips from local walk-in and unguided boat anglers whose relatively lower travel costs might be partially compensated by the promise of an incentive payment.

Second, a harvest incentive may increase the average number of brown trout caught per trip by encouraging anglers to spend more hours on the water or to choose fishing locations, methods, or gear better suited to targeting brown trout. The handful of syntheses on harvest incentive design suggest that these programs perform best in systems where the target species is not wide-spread and is easy to find and identify (Hassall & Associates P/L, 1998; Pasko & Goldberg, 2014; U.S. Department of the Interior. Invasive Species Advisory Committee, 2014). Lees Ferry brown trout are a localized stock, but some Lees Ferry anglers may have trouble locating and catching brown trout. Walk-in anglers cannot access brown trout as easily as boating anglers (only 0.83% of walk-in anglers caught at least one brown trout in 2019 versus 8.91% of boat anglers), and so have limited capacity to have their catch rates impacted by the incentive program. Catch-per-trip may also increase if the harvest incentive induces a compositional shift within the fishery, by drawing a new cohort of highly skilled anglers into the fishery or by incentivizing the existing angler-base to learn by doing. I also know that anglers using spin gear have historically been more likely to catch brown trout than anglers using fly gear. In 2019, 11.27% of anglers using only spin gear caught at least one brown trout, while only 4.33% of anglers using only fly gear caught any brown trout. Assuming that Lees Ferry anglers on boat trips know where and how to catch brown trout and that they are incentivized to do so by the program, I would expect to see those anglers fishing longer hours per-day and using spin gear relatively more often than fly gear in response to the program.

Finally, a harvest incentive may convince anglers to retain more of the brown trout that they catch in what has historically been a catch-and-release fishery.[49] Hassall & Associates P/L (1998) point out that the target of a harvest incentive must be seen as a pest species by a critical mass of potential harvesters in order to be effective. However, in a meeting I attended with program administrators and local angler guides, the guides insisted that their clients enjoy catching and releasing brown trout, do not see it as a pest species, and do not want its population controlled. This program could increase retention rates, then, either by drawing in relatively more trips by unguided boat anglers, who are predisposed to retain more fish (unguided and guided anglers retained 31% and 0% of caught brown trout in 2019, respectively), or by convincing the angler guides and their clients that Lees Ferry brown trout are a pest. However, given that the humpback chub that this program is designed to protect are over 100 river kilometers downstream from Lees Ferry, the message that Lees Ferry brown trout need containing will likely be a hard-sell. In fact, from November 2020 - June 2021, only six of 518 program participants were on guided trips, which suggests that guided anglers have been largely untreated by the program.

[49] In 2019, only 18% of caught brown trout and 1.5% of caught rainbow trout were retained.

Retention behavior is also closely aligned with gear use, with fly anglers retaining 0% and spin anglers 30% of caught brown trout in 2019. Therefore, if the program encourages a compositional shift away from fly fishing and toward spin fishing, both catch and retention rates for brown trout may increase. The program could still fail to increase average retention rates if, upon arriving at the fishery, anglers find it too difficult to participate in the program. However, the process of turning in a brown trout for payment is low friction, and not likely to stifle retention rates. To receive payment for any retained brown trout, anglers must bag the head and entrails of those fish and provide their mailing address on a data card.[50] The bagged fish and data card must then be dropped into a clearly-marked, tamper-proof freezer outside of the Navajo Bridge Interpretive Center, which every angler must drive past in order to exit the recreation area. Bags, data cards, and writing utensils are available at several cleaning stations near the boat launch, at the downstream walk-in point, and adjacent to the program freezer.

4.4 Data

4.4.1 Lees Ferry Fishing Data

We use daily, angler-level data on fishing behavior and outcomes from the Arizona Game and Fish Department (AZGFD) Lees Ferry creel survey (January 2016 - May 2022) to estimate the impact of the program on brown trout landings, as well as the three behavioral margins (trips, catch-per-trip, and retention rate) that comprise

[50]Anglers are asked to provide other sociodemographic information and data on where they caught the brown trout they are turning in and how long those fish were on these data cards. However, they do not need to provide this additional information to receive payment.

landings (Rogowski & Boyer, 2022). The AZGFD creel survey is an angler intercept survey that is administered according to well-documented, site-specific protocols at select U.S. recreational fisheries. At Lees Ferry, a single creel technician interviews anglers at the boat launch and the walk-in point from noon until 6:00 pm on two weekdays and four weekend days each month.[51] For the first 16 months of the incentivized harvest program (November 2020 - April 2022), USGS provided an additional eight weekday and two weekend days of supplemental creeling effort each month.

On any given creel day, the creel technician collects data on the number of people fishing, as well as angler-specific data on the number of rainbow and brown trout caught, and whether those fish were released or retained. I use these data to investigate any potential program-induced changes in trip counts, catch rates (number of rainbow or brown trout caught by an angler on a given day), and retention rates (percent of caught rainbow or brown trout that each angler retained.) The technician also records each angler's gender, age, and home zip codes, the number of fishing trips they have taken to Lees Ferry that year, how many hours they spent fishing that day, the type(s) of fishing gear they used (fly, spin, or both), and which species (rainbow trout, brown trout, or both) they were targeting. I use the information on hours fished and gear use to help explain how and why catch rates changed after the program treatment.

In order to get an accurate measure of how trip-taking did or did not change in response to the program, I cannot simply use daily interview counts as a proxy for trips. Lees Ferry is only ever staffed by a single creel technician on any given creel day, and that person must split their surveying efforts between the boat launch

[51]Creel technicians may leave before 6:00 pm if the weather is bad enough to deter anglers, or if the sun has set and they see no other anglers to interview.

and the walk-in site 1.2 miles away by car. Therefore, the creel technician may miss anglers coming off the water at the boat launch while conducting interviews at the walk-in, and vice versa. If the program was successful at increasing daily trips, then the technician may miss relatively more anglers while splitting their time between the two sites post-treatment, which would cause me to underestimate a positive program effect on trips. Instead of interview counts, then, I use supplemental count data that the technician records for each creel day to estimate total daily trips.

At the boat launch, the creel technician counts the number of anglers interviewed, plus anglers missed (anglers who the technician sees leaving the fishery but does not manage to intercept) and anglers refused (anglers who the technician can access but who refuse to be interviewed.)[52] The sum of anglers interviewed, missed, and refused is the number of *anglers observed* at the boat launch. The technician also records the total number of fishing boats that those observed anglers were in (*boats observed*). Finally, the technician keeps a daily tally of fishing trailers in the parking lot (*fishing trailers*). I first estimate *mean anglers-per-boat* from 2018 through mid-2022 as *anglers observed* divided by *boats observed*.[53] *Fishing trailers* reveals how many total boats—observed and unobserved—were out fishing on any given creel day. So, I estimate daily visitation as *fishing trailers* times *mean anglers-per-boat*.

The creel technician also counts anglers at the walk-in, but I do not use data from the walk-in in this study. This is because brown trout do not usually move far enough downstream for the walk-in anglers to access. Therefore, they are not potential contributors to program success.

[52]Anglers are most often "missed" when multiple boats come off the water at one time, leaving the single creel technician with insufficient time to reach everyone before they depart.

[53]From the beginning of 2018 through early May of 2022, there were an average of 2.32 observed anglers for every boat that came in.

Every angler who turns in a brown trout for payment fills out a data card on which they provide contact and basic demographic information, reveal whether or not they were on a guided fishing trip, and list where each brown trout turned in was caught and how long the fish were. Because these cards are dated, I not only have all of the angler-provided information, but also know how much money the angler was paid per-fish. Additionally, NPS tells me whether or not a PIT tag reward was ultimately issued for any of the fish that were turned in for payment. Furthermore, any additional rewards from the bonanza were publicized.

4.4.2 Lees Ferry Fishery Conditions

Demand for fishing trips may fall when the fishery is relatively more costly (in terms of time or money) to access, or if the fishing experience is made unpleasant either by extreme environmental conditions or by anglers failing to encounter, and therefore catch, many fish. I use data on national average cost of all fuel types and grades ($/gallon) to control for access cost in my trip-margin analysis (U.S. Energy Information Administration, 2022), and include a vector of calendar controls to absorb program-independent temporal variation in behavior across all three margins of analysis. To account for changes in fishing experience, I use several hydrological and meteorological variables as controls across my analyses.

4.4.2.1 Calendar Controls

We include dummy variables for *year, season, day-of-week, holiday,* and *weekend* in my analyses. These calendar date controls soak up changes in landings due to changes in trip-taking or in seasonal changes to population biology. For example, Lees Ferry brown trout become more vulnerable to capture as they move up on the spawning beds from November - January each year. Plummeting air temperatures make fishing at Lees Ferry less popular during those same months and into early spring, meaning that failure to account for seasonal and/or monthly variability might introduce bias into the model. Similarly, day-of-week, weekend, and holiday dummies control for the likely possibility that more anglers go fishing when they have built-in breaks from work. While increased trips may increase landings through that selection effect, it may also cause sufficient congestion on the river to lower average catch rates.

4.4.2.2 Hydrological Data

The Lees Ferry fishery is in the tailwaters of the Glen Canyon Dam, and can thus experience dramatic swings in water flow rate, depth, and temperature. For instance, the Bureau of Reclamation periodically runs high flow experimental releases (HFE) from Glen Canyon Dam to redistribute sediment below the dam. HFEs can impact brown trout immigration and spawning rates in Lees Ferry (Runge et al., 2018), thus impacting the rate at which anglers encounter brown trout. Furthermore, very high or low flows can make fishing less pleasurable, or even unsafe; boating anglers who are inexperienced or less familiar with the river topography of Lees Ferry may be overwhelmed by a strong current, or caught off-guard by large rocks and other hazards that appear when the water is low. Similarly, water temperature may impact the fishing experience by impacting the metabolism, feeding behavior, or population biology at the fishery. Brown trout are more resilient to higher water temperatures than are rainbow trout (Runge et al., 2018), so changes in water temperature will impact the population balance within the fishery, which will in turn impact encounter rates and landings-per-trip for both species. I source daily average discharge (cfs) and water temperature data at Lees Ferry from a USGS meter (United States Geological Survey, 2021).

4.4.2.3 Weather Data

Both rain and extreme daily temperatures could diminish the fishing experience, and heavy precipitation may obscure the water surface, making it hard to target fish. Therefore, I source mean daily air temperature and precipitation data for Lees Ferry from Oregon State University's PRISM Climate Database (PRISM Climate Group, Oregon State University, 2021).

4.4.3 COVID-19 Induced Behavioral Changes

Recent reports suggest that recreation participation and value declined in response to the pandemic, but that the impact was heterogeneous across user-types and activities (Landry et al., 2021; Rice et al., 2020). Thus, COVID-19 may have impacted brown trout landings at Lees Ferry by increasing or reducing the number of fishing trips that anglers took to that fishery. Furthermore, if a pandemic-derived desire for remote outdoor recreation drove enough new participants into the fishery, then average per-trip catch rates may have declined due to these new entrants' relative lack of site-specific knowledge. It is essential, then, to control for any impacts that COVID-19 may have had on fishery participation and catch rates and, therefore, landings. However, because the pilot program began well into the COVID-19 lockdown, a dummy variable for the period of the pandemic would soak up any program-induced variability in landings that I want to measure. Furthermore, a pandemic dummy would be inappropriate in that COVID-19 varied in severity and likely would have had a complex effect on fishing behavior that is not reducible to a simple discrete shift. In order to account for a potential "coronavirus effect," I include several time-varying controls in my analyses which are designed to account for pandemic-induced non-stationarity across multiple scales.

4.4.3.1 COVID-19 Metrics

The Blavatnik School of Government and Oxford University released country-level indices regarding stringency of government response to COVID-19 at the beginning of 2020 (Hale et al., 2021). The index is calculated using eight ordinal containment and closure codes plus one ordinal public information campaign code. This daily time series is still being updated, and is released alongside daily updated counts of total confirmed COVID-19 cases and deaths to-date. I use the stringency index, case counts, and death counts for the US to capture the dynamics of COVID-19 severity and policy response on a national level over the course of the incentivized harvest program. All three variables begin with values of zero and have at least 8 months of daily, non-zero data prior to the onset of the pilot program. I transform each of these variables to within-week changes in order to better capture the inertia of the pandemic in my analyses.

4.4.3.2 Monthly recreation participation

It is likely that there were region-specific changes to recreation participation, in general, in response to COVID-19. As the pandemic oscillated in severity and people become more or less responsive to changes in infection and death rates, they likely took relatively more or fewer recreation trips to parks in their home region. Therefore, I use monthly recreation visit counts data from every National Park Service site in the Intermountain region to capture region-specific COVID-19 impacts on recreation trips in my analyses ("National Park Service Visitor Use Statistics", n.d.). The 2022 data are preliminary, and the final published visitation counts may vary slightly from those used in this paper.

4.4.3.3 Google Trends data

Because the impact of COVID-19 on recreation participation was heterogeneous across activities, I use monthly search frequency data for several fishing-related search terms to account for any activity-specific pandemic effects that may have impacted Lees Ferry visitation. I download lagged (by one and two months) and unlagged data from Google Trends for four search terms of varying granularity that are relevant to the Lees Ferry fishery (Google Trends, n.d.). These search terms are: "outdoor recreation," "fishing license," "fly fishing," and "trout fishing."

4.5 Methods

We estimate five separate models in order to investigate the direct impact of the program on brown trout landings, as well as any indirect effects of the program on rainbow trout landings. My models estimate the program's impact on trip-taking, catch-per-trip, and retention rates amongst unguided boat anglers. Because they did not participate in the program, I treat guided boat anglers as an untreated control throughout my analyses. The following description of methods are written in terms of brown trout, but the procedure I used to estimate the impact on rainbow trout is identical. Note that the program's kick-off date in November 2020 occurred during a time of peak COVID-19 restrictions. As a result, NPS was unable to host a kick-off event or do much in the way of advertising for the program at its beginning. It wasn't until the base bounty raised from $25 to $33 per fish in March 2021 that advertising for the program began in earnest, especially since NPS began to advertise their first harvest incentive bonanza event, which ran throughout the month of April 2021, around that same time. Therefore, I treat the program start-date as March 1, 2021, throughout my analyses, and drop all data from the true start date of November 11, 2020, through the end of February 2021 in all of my analyses to avoid biasing my results.[54]

4.5.1 Margin 1: Trips

As guided anglers largely did not participate in the incentivized harvest program, I assume that total additional trips equals the number of trips to Lees Ferry taken by

[54]Estimation results including data from November 2020 - February 2021 are in the Appendix.

unguided boat anglers above what they would have taken absent the program; guided anglers are not included in my trip margin evaluation.

The Lees Ferry creel samples a subset of anglers who come back to the boat ramp between noon and 6 pm; technicians are not able to interview every angler on a given day. Furthermore, the fraction of anglers sampled varies by day and by creel technician. There are two reasons to believe that the average within-day sampling fraction differs significantly pre- and post- program implementation. First, prior to the program, the creel was mostly administered by a single, AZGFD-contracted technician, but USGS employees began supplementing the creel when the program began. The AZGFD and USGS creel technicians have different levels of experience and—likely—motivation.[55] Second, if the program brought in additional visitors, then it is more likely that any one creel technician might be unable to interview a larger proportion of the total anglers. For these reasons, number of anglers interviewed is an imperfect proxy for total visitation. Therefore, I calculate daily trips according to the procedure described in section 4.4.1.

In order to accurately estimate additional brown trout harvest, I would ideally perform a difference-in-differences (DID) linear regression to compare changes in trips per day during the pilot program between Lees Ferry and one or more counterfactual fisheries that would have been similarly impacted by COVID-19 and other time-varying factors, but that did not receive a separate policy treatment during the study period. However, data collection at Lees Ferry is unique in its quality, frequency, and consistency, and there are no other fisheries in the U.S. Intermountain Region with suitable data to serve as a counterfactual in a DID or synthetic DID approach.

[55] The USGS technicians were providing additional creel days to bolster a program-related research agenda. During winter months, the AZGFD tecnician is not a researcher, but an avid angler. During the rest of the year, AZGFD staff serve as creel technicians.

Instead, I use a machine learning (ML) algorithm to construct a counterfactual from historical Lees Ferry data and a set of time-varying controls, then use daily fishing trip predictions from that counterfactual to perform a routine DID estimation. Prest et al. (2023) tested the ability of three common ML algorithms to replicate the treatment effect identified using a traditional DID estimation approach, and found all three algorithms up to the task even when trained using only data from the treated group. Thus, an ML-constructed counterfactual trained only on historical Lees Ferry data or on that historical data plus additional time-varying controls should allow me to isolate the IH program's true treatment effect.

4.5.1.1 Constructing a Counterfactual

We use a Least Absolute Shrinkage and Selection Operation (LASSO) algorithm to generate counterfactual daily trips predictions, which is one of the three algorithms that Prest et al. (2023) showed capable of isolating the true treatment effect when used to generate a DID counterfactual.[56] LASSO is a linear regression approach which estimates regression coefficients such that the residual sum of squares (RSS) plus the LASSO tuning parameter λ times the ℓ_1 norm of the standardized coefficient vector is minimized (James et al., 2021). In other words, the LASSO coefficients, $\hat{\beta}^L_\lambda$ minimize

$$\sum_{i=1}^{N}\left(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij}\right)^2 + \lambda\sum_{j=1}^{p}|\beta_j|. \tag{4.1}$$

[56]We also tried using ML to construct counterfactual prediction models for catch per-trip and retention rate. However, without catch and harvest data from a comparable recreational fishery, the resulting models were too sparse to generate reasonable counterfactual predictions of those outcome variables; they performed only as well or slightly better than using the historical means of catch and retention rates. Since catch-per-trip and retention rate are less likely to be affected by COVID-19 than trips, however, it is less important that those margins be estimated using ML counterfactuals.

When $\lambda = 0$, $\hat{\beta}^L_\lambda = \hat{\beta}_{ols}$. As λ gets larger, the model gets more regularized, with certain coefficients getting pushed near or even to zero, effectively dropping them from estimation. Regularizing the model is important to avoid issues of overfit, which can hurt out-of-sample predictive power in the same way that under-specification would. The process of selecting λ to optimize for out-of-sample predictive power is called cross validation (CV.) Specifically, I use K-fold CV in which I feed-in training (pre-treatment) data, and the observations from that data are assigned to one of $K = 10$ test folds. As LASSO only considers linear functions of the provided variables, I include all Lees Ferry training data (i.e., historical daily trip counts and the controls described in Sections 4.4.2 and 4.4.3), plus the full set of squared terms and interactions for those data in the initial model for CV. For each potential value of λ, the test folds are iteratively withheld from the training data then compared to the predictions generated by the trained LASSO model to assess out-of-sample predictive power. I test 100 λ values using the *glmnet* package in R, and select the tuning parameter whose K folds result in the smallest root mean square error (RMSE), and thus exhibits the best out-of-sample predictive power. I then use this minimum RMSE model to predict trips per-creel-day over the entire pre- and post-treatment study period. These $\hat{y}$ values are the counterfactual, untreated observations that I use in the DID estimation. Figure 13 displays average number of daily predicted and observed trips by month before and after the program's March 2021 kickoff.[57] This pretrends graphic suggests that the ML counterfactual does a good job of accurately predicting daily trips before the incentive treatment, which builds confidence that a DID estimation using this counterfactual should accurately estimate additional trips. The one exception to this

[57]November 2020 - February 2021 are omitted from the figure as these months were after the program's official start date, and were therefore potentially treated.

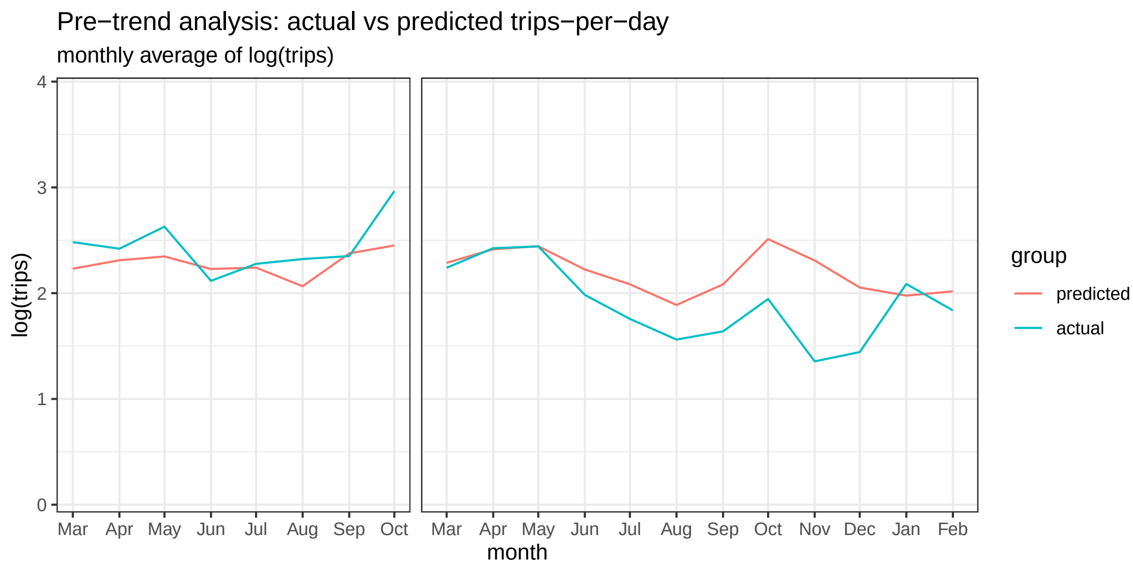

Figure 13. Mean Observed Lees Ferry Daily Trip Counts (Actual) and Daily Trip Counts Predicted by the ML Counterfactual (Predicted) by Month from March 2020 through December 2021. The vertical break in the graph occurs between the last untreated month and the March 2021 kickoff.

finding is October 2020, where the LASSO model appears to have under-predicted trip-taking. I ran a robustness check in which I dropped all October 2020 data and re-ran the CV procedure to ensure that the inclusion or exclusion of that month did not significantly change my DID regression results. My estimation results were robust to the removal of October 2020, which bolsters my confidence that the ML model does a sufficiently good job of predicting counterfactual trip-taking. Furthermore, even if an under-prediction in the final pre-treatment month had biased my results, it would suggest that the program underperformed even more than my estimates suggest.

4.5.1.2 The DID Model

The DID estimator, which was first employed by Card and Krueger (1994), is an increasingly popular policy evaluation tool. In this case, I are interested in estimating the program's impact on trips per creel day to Lees Ferry. In order to estimate this effect, the DID estimator makes use of pre- and post-treatment data from the study site and a comparable counterfactual site to calculate the mean effect of the policy intervention on the treated site (i.e., the *average treatment effect on the treated* (ATT)).

There are several key assumptions underpinning the validity of DID estimation. First, the control must not be indirectly treated, which would bias the estimated ATT (Cunningham, 2021). This stable unit treatment value assumption (SUTVA) is not violated, since the control is predicted using a linear regression model built entirely with pre-treatment data. The second assumption implicit in DID estimation is the parallel trends assumption, which requires that any time-variant factors other than the treatment variable impact the treatment and control groups equally in the absence of treatment (Angrist & Pischke, 2009). The purpose of CV in the ML procedure is to maximize out-of-sample predictive ability, or to select the regression model that should do the best job, on average, of predicting trip-taking in the absence of treatment. While I cannot test this assumption directly, I can perform a pre-trend analysis with the reasoning that if trip-taking varied proportionally in the treatment and control groups pre-treatment, then they likely would have continued to do so into the future absent treatment.

We estimated ML counterfactuals for trips and log(trips) and found that the latter model performed better than the former in pre-trend analysis. This is likely because the linear trips prediction model was sparse, containing only a single interaction variable. The log model, on the other hand, utilizes 21 independent variables to predict log(trips), and better captured variability in trip-taking as a result.[58] Figure 14 is an event study plot of average daily log(trips) by month in the pre- and post-treatment periods. Any controls are implicit in the ML counterfactual; this event study looks only at how log(daily trips) differs between the treated data (observed trips to Lees Ferry) and the untreated counterfactual (the ML predictions for log(trips) per day.) This graphic suggests that the parallel trends assumption holds, as it fails to find significant differences in predicted and actual log(trips) before the program kick-off. As discussed above, the last pre-treatment month is October 2020, while the first treated month is March 2021.

$$log(y_{it}) = \beta_0 + \beta_1 Post_t + \beta_2 Tmt_i + \beta_3 Post_t \times Tmt_i + \beta_4 Post_t \times Tmt_i \times X_t + \varepsilon_i \quad (4.2)$$

In Equation 4.2, y_{it} is trips per creel day at fishery i on day t. In this case, i denotes either observed daily trips to Lees Ferry y or the $\hat{y}$ counterfactual from the LASSO prediction model. I normalize trips by creel day to control for potential changes in creeling effort at Lees Ferry. $Post_t$ is a dummy variable that equals 1 if an observation occurs on a post-treatment day (i.e., after the onset of the pilot program) and 0 otherwise. Similarly, Tmt_i equals 1 if an observation is from the treatment fishery (observed Lees Ferry trips) and 0 otherwise (ML-predicted Lees Ferry observations.) The parameter of interest here is β_3, which is the average treatment effect on the treated (ATT). If β_3 is greater than zero and statistically significant, then that suggests

[58]There are no zero trip days in my data, so I did not need to perform any additional transformations before logging trips.

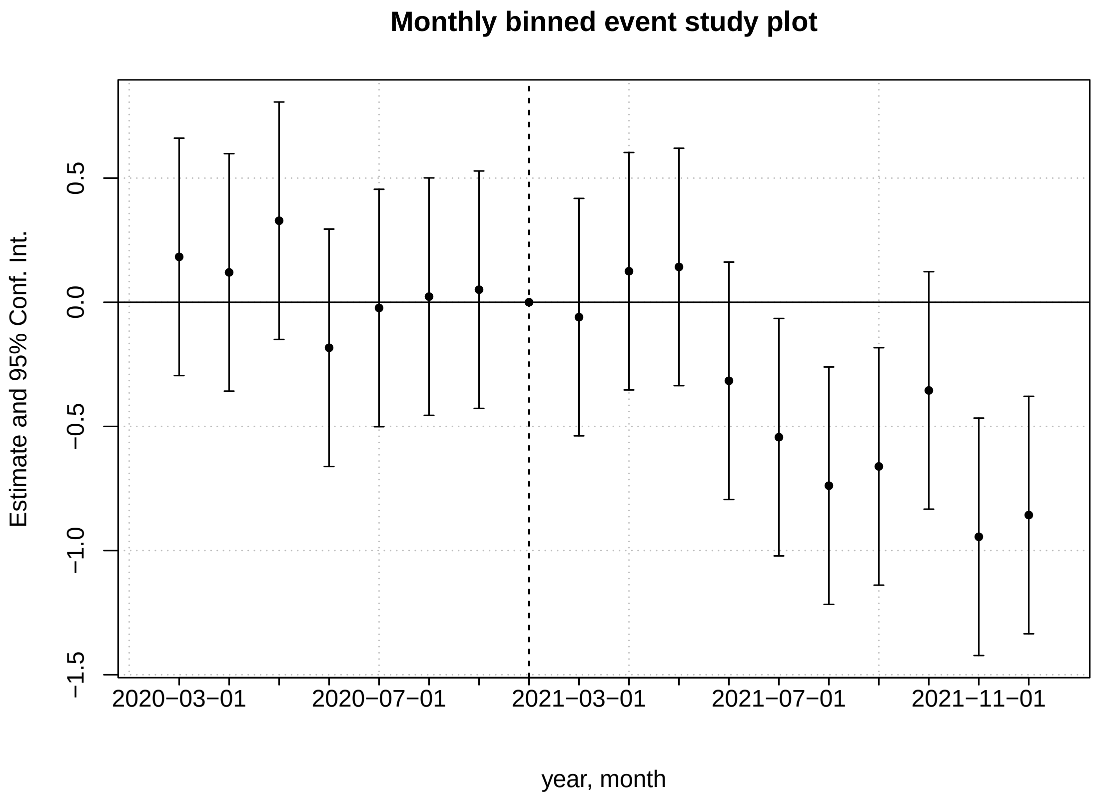

Figure 14. A Monthly Event Study Graph of the Log of Daily Trips Pre-treatment and Post-treatment. The dashed vertical line indicates the last pre-treatment month, October 2020.

the program caused daily trip-taking to increase. Conversely, if β_3 is near zero and not statistically significant, then the program had no effect on daily trips.

We not only want to know how the existence of the pilot program impacted visitation rates, but also how changes in the program's design (through the introduction of new payment levers) may have changed trip-taking behavior relative to the baseline program values. In equation 4.2, X_t is a vector of three payment levers whose effects I are interested in measuring. These levers are: 1) *bonanza*, or a dummy variable that equals one if there was an active program bonanza on day t; 2) *3 fish bonus*, which is a dummy variable that equals one if anglers could receive a $50 bonus for every third brown trout submitted to the program on day t; and 3) *pit bonus*, which is an indicator for whether or not the \$300 pit tag bonus was active on day t.

4.5.2 Margin 2: Catch-Per-Trip

We use trip-level creel data on brown trout caught, whether a trip was guided, and time-varying controls to perform a DID evaluation of whether and how the pilot program impacted catch-per-trip of brown trout. Rather than constructing a ML counterfactual for the catch margin, I leverage the fact that guided anglers were untreated and faced the same fishing conditions as unguided anglers to justify using Lees Ferry guided anglers as the untreated counterfactual for this margin.

Guided anglers as a control group for catch in the absence of the program satisfies the SUTVA assumption, because I know that fewer than 1% of program participants were on guided trips, which suggests that a strong catch-and-release ethic insulated guided anglers from being treated by this program. Furthermore, individuals who pay several hundred dollars for a guided trip on top of their airfare and lodging costs are fundamentally different from anglers who drive their own boats to the Lees Ferry fishery—they may be less likely to be tempted by a nominal retention reward than unguided anglers.

At first glance, guided anglers as a control group do not satisfy the parallel trends assumption. Since 2020, guided anglers have caught relatively more brown trout than unguided anglers in winter months when brown trout are on their spawning beds, and therefore more vulnerable to capture (see Figure 15). It appears that the guides' knowledge of the fishery's population dynamics advantages their clients especially during spawning season, which results in a clear violation of the parallel

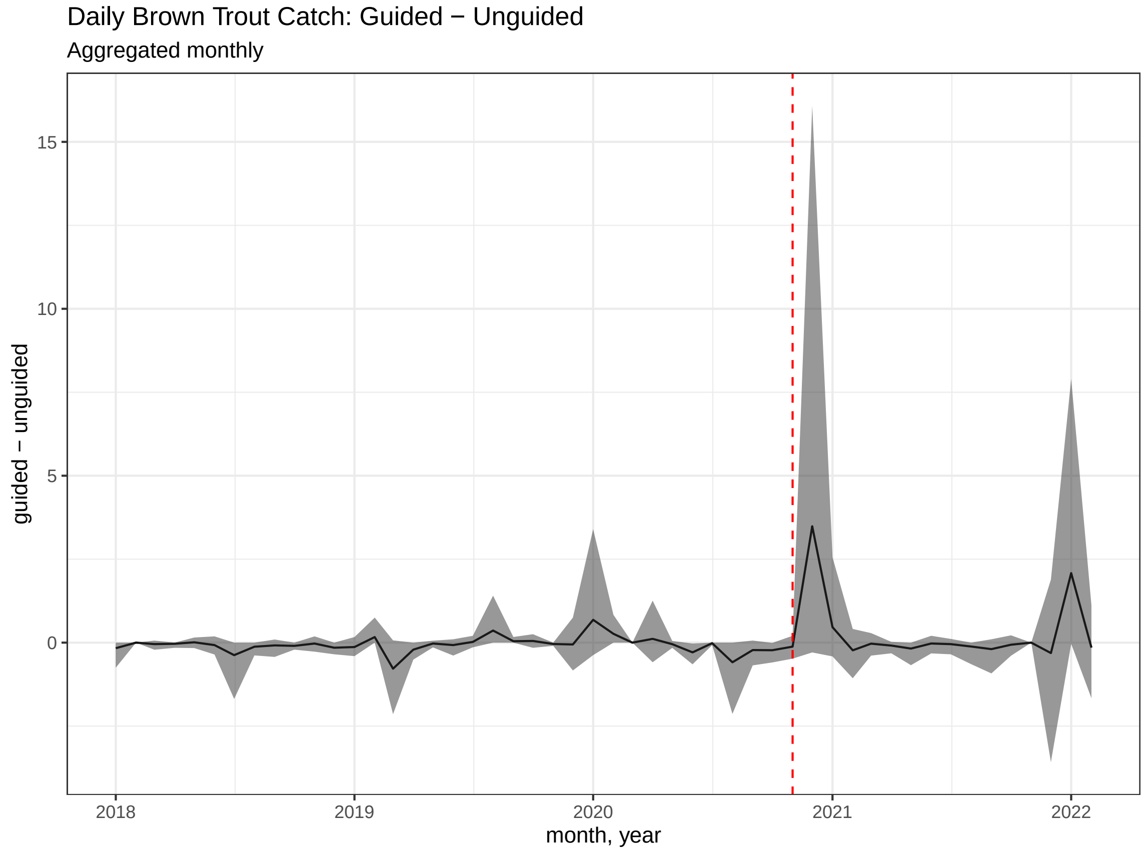

Figure 15. Distribution of Difference in Brown Trout Catch per Trip by Month Between Guided and Unguided Anglers. Solid line represents mean catch-per-trip while the shaded region captures the 95% confidence intervals. Red dashed line denotes program onset.

trends assumption. Once I account for this differential seasonality in catch rates across the guided and unguided groups by including separate seasonality controls for guided anglers, the parallel trends assumption is satisfied. Figure 16 is an event study of average catch-per-trip, binned monthly. I see that there are no significant treatment effects pre-treatment, which suggests that this design satisfies the parallel trends assumption.

We estimate a Poisson DID model of brown trout caught-per-trip, where β_3 is the ATT, X_t is the same vector of price levers as in the trips model, and D_{it} is a vector of

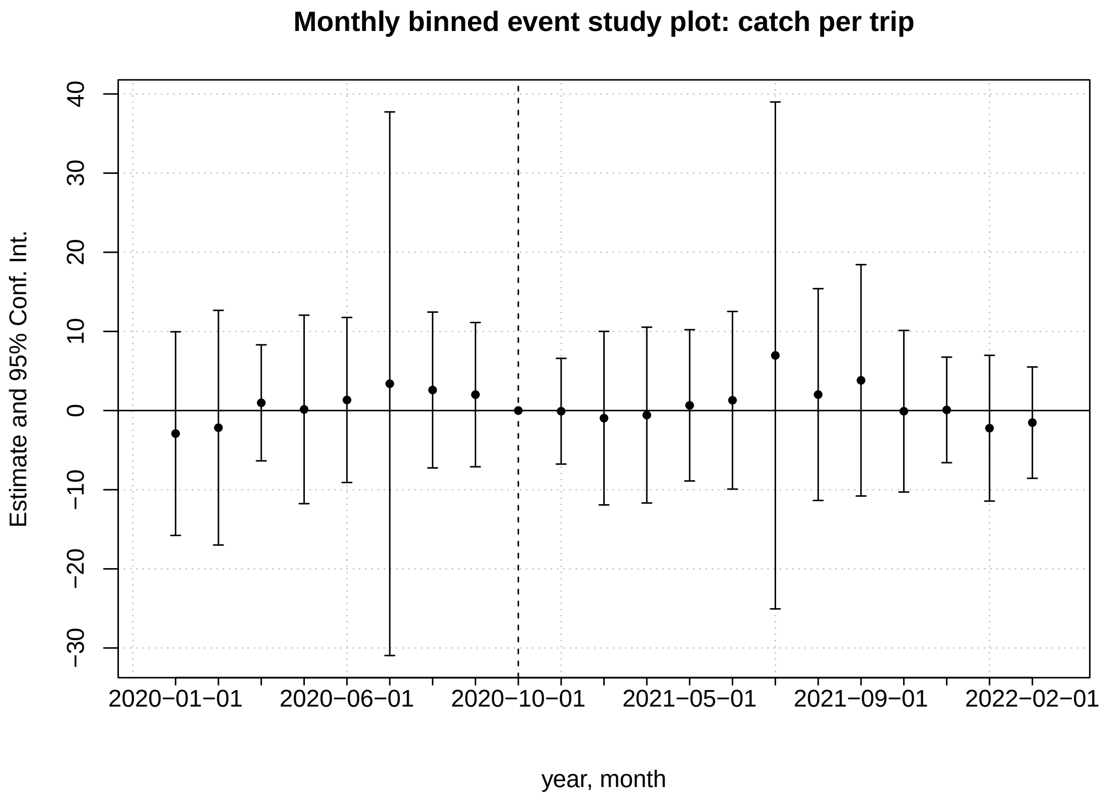

Figure 16. A Monthly Event Study Graph of Catch per Trip Pre-treatment and Post-treatment. The dashed vertical line indicates the last pre-treatment month, October 2020. Missing pre-treatment months were also insignificant, but had sufficiently large confidence intervals to make all other months impossible to see, and so were removed from the graphic for clarity.

time-varying controls meant to absorb seasonal, treatment-independent differences in catch rates between guided and unguided anglers.

$$
\begin{aligned}
E[y_{it}|Z] = exp(&\beta_0 + \beta_1 Post_t + \beta_2 Tmt_i + \beta_3 Post_t \times Tmt_i + \\
&\beta_4 Post_t \times Tmt_i \times X_t + \beta_5 D_{it})
\end{aligned}
\tag{4.3}
$$

While brown trout catch rates in Lees Ferry exhibit over-dispersion ($mean = 0.1312$, $var = 0.3861$ in 2019), I do not explicitly account for this in my estimation approach.

The Poisson estimator is a member of the linear exponential family, which means quasi-maximum likelihood estimates (QMLE) of the conditional mean will still be consistent, even if the underlying distribution of the data is not correct (Cameron & Trivedi, 2010b). I do, however, estimate robust standard errors to account for this distributional mismatch (Cameron & Trivedi, 2010a). Furthermore, the Poisson has the advantage relative to other QMLE estimators of providing a clear, easily interpretable semi-log interpretation without distorting the many zero catch observations in my data (Wooldridge, 1999).

4.5.3 Margin 3: Retention Rate

Unlike the other two margins of brown trout harvest, I do not take a DID approach to estimating additionality for retention rate for two reasons. First, while untreated by the program, guided anglers are not a suitable counterfactual to unguided anglers for this margin of analysis because guided anglers retain virtually zero brown trout per-trip before and after the program launched. Second, I assert that anglers' retention rates are unlikely to be impacted by COVID-19, hydrology, and other sources of non-stationarity within the fishery, making a counterfactual regression approach unnecessary. I instead estimate a simple before-after regression of program-induced increases in retention rate for treated (i.e., unguided) Lees Ferry anglers.

We estimate a fractional logit (first used in Papke and Wooldridge (1996)) of the proportion of brown trout retained for trips on which at least one brown trout was caught against a post-treatment dummy ($Post_t$), a vector of payment levers (X_t), and a vector of time-varying controls (D_t) (see Equation 4.4).

$$E[retention\ rate|Z] = \frac{exp(\beta_1 Post_t + \beta_2 X_t + \beta_3 D_t)}{1 + exp(\beta_1 Post_t + \beta_2 X_t + \beta_3 D_t)} \tag{4.4}$$

Like the Poisson, the fractional logit is a QMLE estimator, so I estimate heteroskedasticity robust standard errors to ensure consistent estimates.

4.6 Results

By and large, my regression results suggest that the program failed to induce many additional brown trout landings because while one aspect of the bounty policy in particular likely convinced anglers to retain relatively more of the brown trout that they did catch, it neither brought additional trips into the fishery (and in fact may have decreased daily trip-taking) nor increased the number of brown trout that the average Lees Ferry angler caught. Similarly, the program caused, if anything, a reduction in the number of rainbow trout landed. Therefore, even though the program failed to meet its brown trout removal objective, it also did not increase harvest pressure on the fishery's non-target species.

4.6.1 Trips

Table 12 presents the estimation results of two DID models. The first model is a basic DID regression of the ATT, while model two also includes interactions between this DID estimator ($Post \times Tmt$) and indicators for certain pricing design levers. Model 1 rejects the hypothesis that the harvest incentive had no effect on daily trip-taking to Lees Ferry, and even suggests that daily trips counts may have

Table 12

DID Regression of log(trips) per day on the March 2021 Kickoff and Subsequent Treatment Levers.

	Dependent variable:	
	log(trips) per day	
	(1)	(2)
Post	0.127	0.097
	(0.080)	(0.082)
Tmt	0.000	0.000
	(0.074)	(0.075)
Post×Tmt	-0.276^{**}	-0.043
	(0.114)	(0.147)
Post×Tmt×bonanza		0.290
		(0.162)
Post×Tmt×3 fish bonus		-0.267
		(0.205)
Post×Tmt×pit tag bonus		-0.209
		(0.176)
Constant	2.085^{***}	2.085^{***}
	(0.052)	(0.053)
Observations	626	626
R^2	0.016	0.030
Adjusted R^2	0.011	0.021
Residual Std. Error	0.701 (df = 622)	0.718 (df = 619)
F Statistic	3.386^{**} (df = 3; 622)	3.186^{***} (df = 6; 619)
Note:		*p<0.1; **p<0.05; ***p<0.01
		Standard errors are heteroskedasticity robust.

fallen post-treatment. This finding is not all that surprising, given how remote and expensive Lees Ferry is to access. In the first year of the program, the average boating angler caught only 0.16 brown trout per trip. Therefore, the expected payout for taking a fishing trip to Lees Ferry would have been much lower than the cost of taking the trip for most anglers, and especially for those unguided anglers who had to pay for gasoline to tow their boat to the fishery. Not only may the bounty have been too low to draw in additional fishers, but existing Lees Ferry anglers may have expected the nuisance of program-induced crowding, and therefore taken relatively fewer trips, which would explain the negative effect on trip-taking.

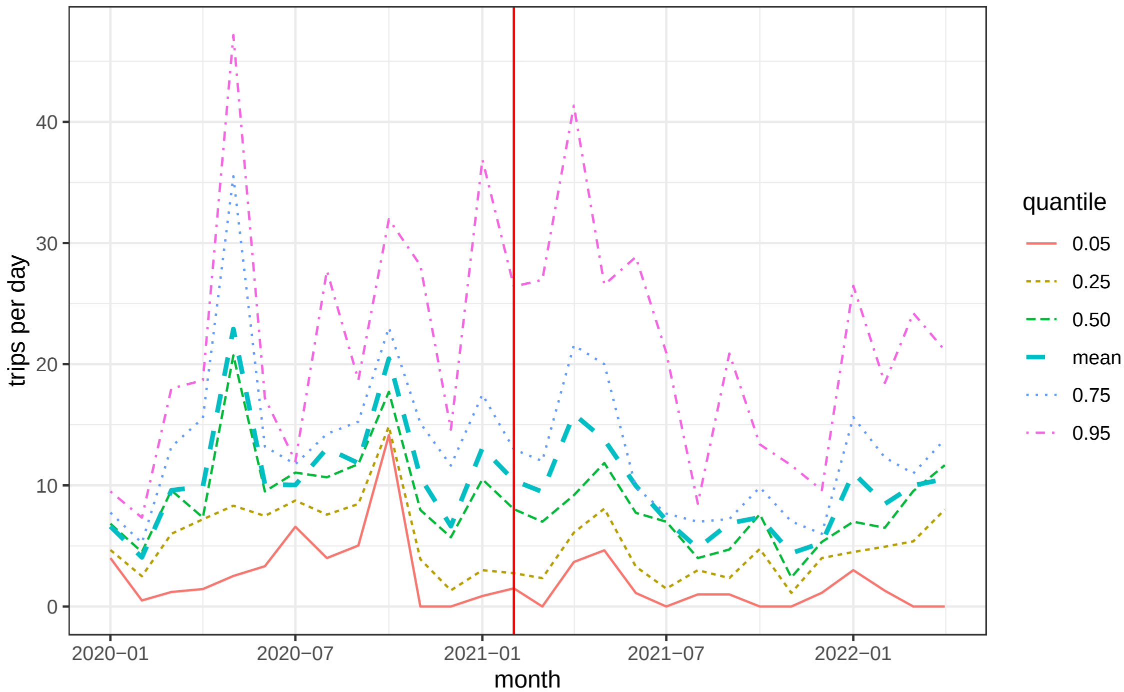

Figure 17. Monthly Distributions of Daily Lees Ferry Fishing Trips by Unguided (Potentially Treated) Anglers. The red vertical line marks the March 2021 treatment date.

The second model in Table 12 fails to reject that the program kick-off and any of the pricing levers to follow had no effect on trip-taking. In other words, while model 1 suggests that the program reduced trip-taking, model 2 reveals that no single design element alone is responsible for this trend. A glance at the raw distribution of trips per day by unguided anglers pre- and post-treatment (see Figure 17) supports the findings of both models; there were similar surges in trip demand in the spring seasons pre- and post-treatment, and the distribution of daily trips is either unchanged or slightly reduced in autumn 2021 relative to the year before. Therefore, it is reasonable to conclude that the ML-derived counterfactual did a sufficiently good job at predicting what trip demand would have been in lieu of the bounty treatment to accurately identify a lack of treatment effect.

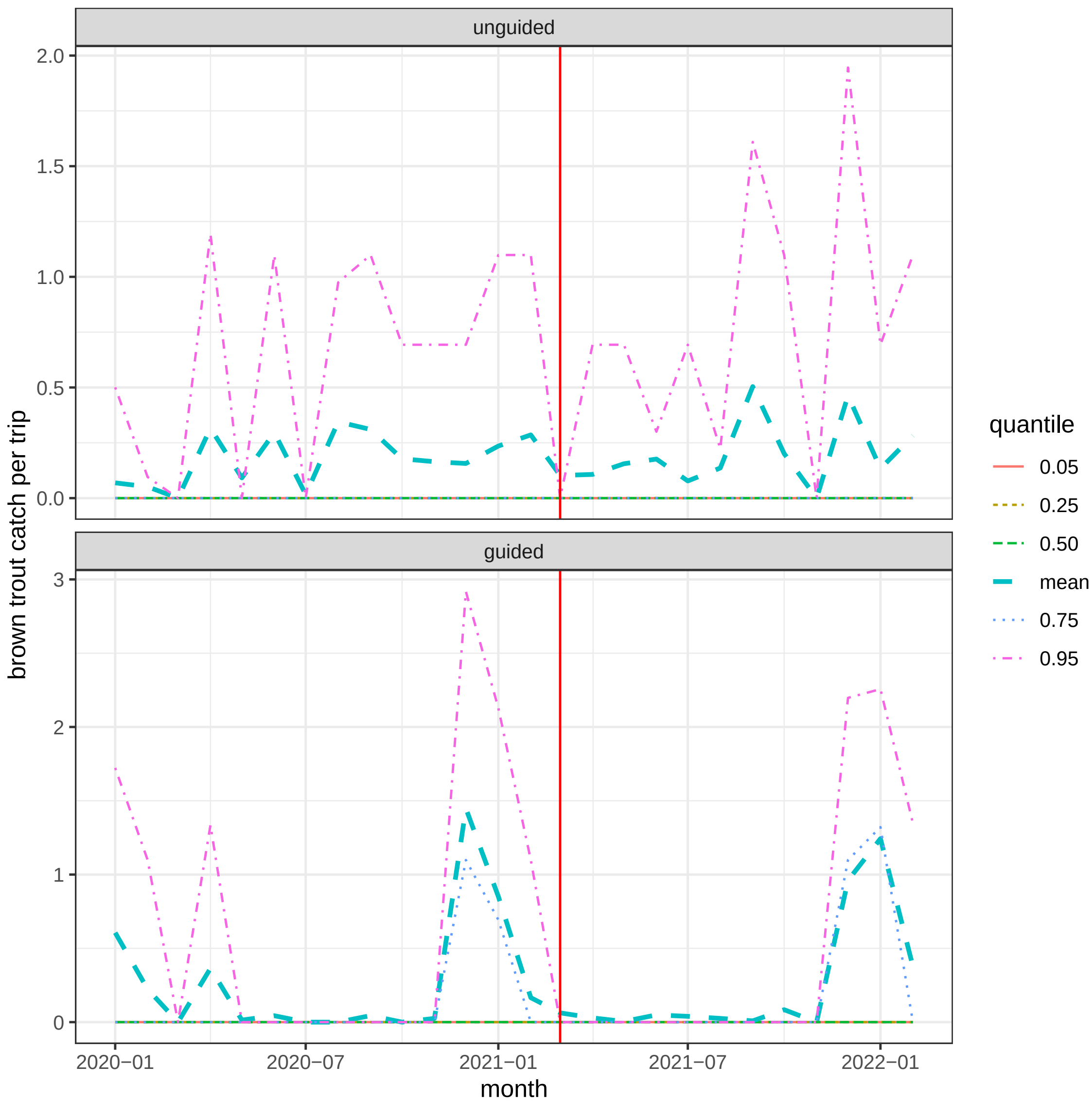

Figure 18. Monthly Distributions of Brown Trout Catch per Trip by Unguided (Potentially Treated) Anglers. The red vertical line marks the March 2021 treatment date.

4.6.2 Brown Trout Catch-Per-Trip

Catch per trip for brown trout does appear to have been impacted by the harvest incentive program and its payment levers, but the overall effect on brown trout landings is ambiguous. In Figure 18, it is clear that while untreated guided anglers experienced the same seasonal trend to their brown trout catch rates pre- and post- treatment (i.e., they still only tend to catch brown trout around the winter spawning time), the potentially treated unguided anglers saw a slight post-treatment change to per-trip catch rates that may or may not be attributable to the program. Specifically, the mean and 95th percentile of trips (in terms of number of brown trout caught) in early autumn (when the pit tag bonus kicked in) and winter (when the second bonanza event ran) may have increased relative to the prior, pre-treatment year. Because I control for guide-specific seasonality in my catch models, the guided anglers should serve as an ideal untreated control group to correctly identify whether or not the mean catch rate of unguided anglers was actually treated by the program.

Table 13 presents two DID Poisson models of brown trout catch per trip on the program's March 2021 kick-off ($Post : Tmt$), as well as on the program's various payment levers. Both models include a vector of seasonal (*season*, $season : Tmt$, *year*), weather (*mean daily air temperature*, *daily precipitation*), hydrological (*mean daily water temperature*, *mean daily discharge rate*), and COVID-19 (weekly changes in *government response stringency*, *cases*, *deaths*) controls in order to control for time-varying factors that might differentially impact guided and unguided anglers' catch rates. Model one includes a simple, linear specification of these controls, while model two includes polynomial specifications of all but the seasonal controls up to degree five such that AIC is minimized.

Models one and two in Table 13 both fail to reject that the three fish and pit tag bonuses had no effect on per-trip brown trout catch. These models also reject that the program had no effect on brown trout catch, and suggest that the overall program effect on this margin was negative. However, these models disagree on which price

Table 13

DID Poisson Regression Results of Brown Trout Catch per Trip on the March 2021 Harvest Incentive Kickoff and Subsequent Payment Levers.

	Dependent variable:	
	Brown trout catch per trip	
	linear controls	polynomial controls
	(1)	(2)
Post	−0.316	2.704***
	(0.358)	(0.579)
Tmt	0.846***	0.711***
	(0.206)	(0.203)
Post×Tmt	−0.565**	−0.154
	(0.203)	(0.236)
Post×Tmt×bonanza	−0.849***	−1.088***
	(0.216)	(0.241)
Post×Tmt×3 fish bonus	−0.122	0.435
	(0.220)	(0.293)
Post×Tmt×pit tag bonus	0.973	0.264
	(0.222)	(0.258)
Constant	−4.488***	−3.135***
	(0.600)	(0.717)
Observations	6,360	6,360
Log Likelihood	−2,946.522	−2,809.435
Akaike Inf. Crit.	5,939.044	5,704.871
Note:		*p<0.1; **p<0.05; ***p<0.01
		Standard errors are heteroskedasticity robust.

lever is responsible for this effect. Model one suggests that the program's March 2021 kick-off decreased brown trout catch per trip by 43%, whereas model two fails to reject that the program's implementation had no effect on brown trout catch rates. Between

Table 14

Fractional Logit Regression Results of Brown Trout Retention Rate on the March 2021 Program Kickoff and Subsequent Payment Levers.

	Dependent variable:	
	Brown trout retention rate	
	linear controls	polynomial controls
	(1)	(2)
Post	0.256	−0.171
	(0.443)	(0.454)
bonanza	−0.785	−0.315
	(0.627)	(0.664)
3 fish bonus	2.323***	2.601***
	(0.721)	(0.758)
pit tag bonus	−1.941***	−2.102***
	(0.726)	(0.760)
Constant	1.459	4.176
	(2.136)	(2.941)
R2	0.156	0.208
Adjusted R2	0.115	0.151
Observations	301	301
Note:		*p<0.1; **p<0.05; ***p<0.01
		Standard errors are heteroskedasticity robust.

these two models, unguided boat anglers saw their daily brown trout catch decrease between 66% and 76% during bonanza events relative to the pre-treatment period.

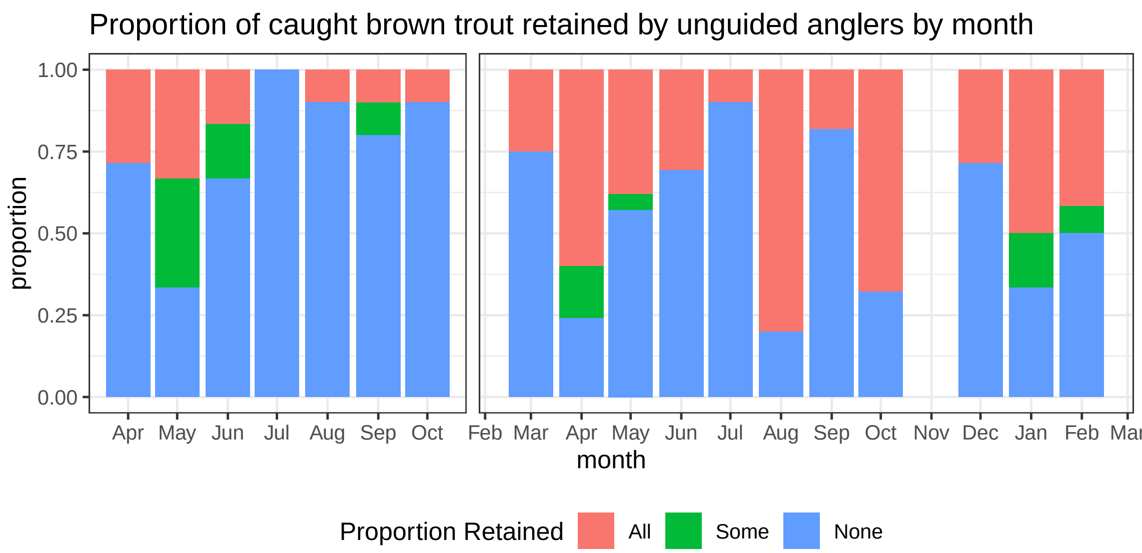

Figure 19. The Proportion of Unguided Anglers who Retained None, Some, or All Caught Brown Trout by Month. The break in the graph indicates the program kickoff with potentially treated months (November 2020-February 2021) removed.

4.6.3 Brown Trout Retention Rates

Table 14 presents the results of two fractional logits of brown trout retention rate on program treatments. Model one contains a vector of linearly-specified controls for whether or not it is a weekend, season, weather, and hydrology. Model two contains those same controls with polynomial specifications up to the third degree for continuous variables such that adjusted R^2 is maximized. While I fail to reject that the program kick-off and bonanza events had no effect on the percent of caught brown trout that unguided boat anglers retained, it appears that the adoption of the \$50 bonus for every third fish in August 2021 increased brown trout retention rates, while the inclusion of a \$300 pit tag bonus a month later apparently lowered them.

Figure 20 displays the average marginal effects (AMEs) of the treatment levers on brown trout retention rates as calculated from models one and two in Table 14.

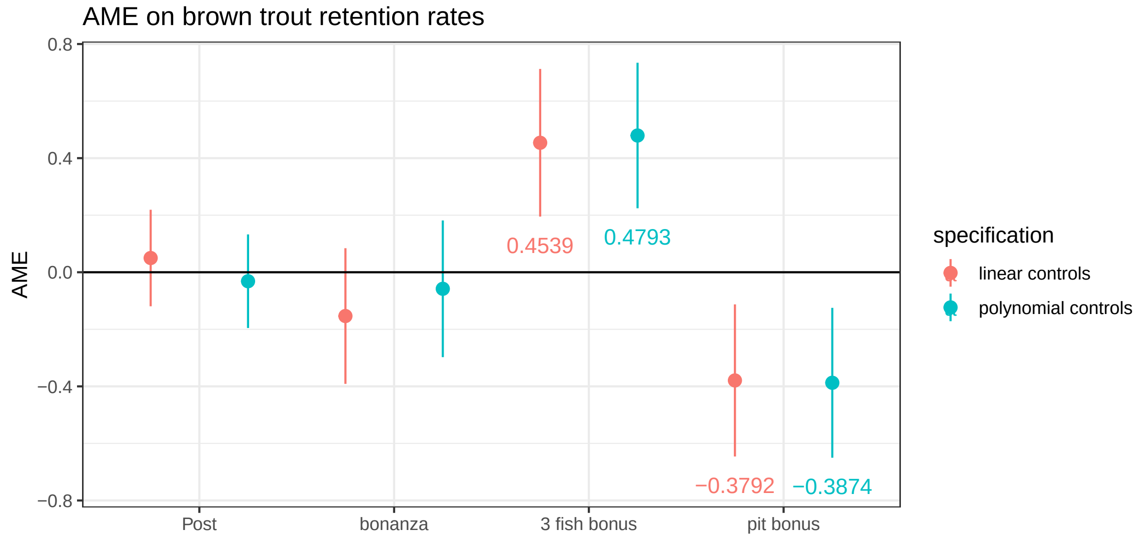

Figure 20. Average Marginal Effects (AME) of Program Treatments on Brown Trout Retention Rates. As estimated in the models in Table 14. The AMEs which are significant at $p \leq 0.05$ have their estimated means listed.

The estimated means of these AMEs are numerically very similar between the two models; the implementation of the three fish bonus increased brown trout retention rates by between 0.45 and 0.48, while the pit tag bonus decreased retention rates by between 0.38 and 0.39. The former result suggests that the intensification incentive of the three fish bonus was likely very effective in incentivizing increased retention; anglers were more likely to retain any brown trout they caught in hopes that they would catch enough fish to collect the $50 bonus.

Pricing levers which reward intensive effort (i.e., those designed to encourage relatively more retention conditional on having taking a trip and caught a member of the target population) may be especially effective in systems like Lees Ferry that boast strong catch-and-release cultures. Unlike trips and catch-per-trip, retention rates have an upper bound—you can only retain as many fish as you catch. Therefore, treatment levers like this three-fish bonus cannot induce additional harvest on the retention margin in systems where it is common to retain most or all of your catch. Figure 19 reveals that most Lees Ferry anglers retained none of their brown trout catch pre-treatment, which means there was sufficiently low retention pre-treatment to make retention rates an effective leverage point for the program. In fact, more anglers retained every brown trout caught post-treatment than before, and that effect is especially visible from August 2021—the month the $50 three fish bonus was introduced—onward.

The apparent negative effect of the PIT tag bonus on retention rates is harder to explain. I do not know how individual anglers judged their own probability of catching a tagged fish. Many anglers may have believed catching a tagged fish to be very unlikely, and thus had low expected payouts for retaining brown trout. NPS has published the number of fish with and without PIT tags turned in each month on their website since November 2020. Anglers could have used these values to form an expectation (for example, in September 2021, the month that the $300 PIT tag bonus launched, seven out of 50 or 14% of brown trout turned in for payment contained PIT tags, resulting in an expected PIT tag bonus of $42 per fish). In reality, very few anglers were likely aware of this data, and even fewer would have done this calculation prior to their fishing trip.

A non-insignificant group of unguided anglers opposed this program on principal; they believe it is wrong to keep a fish for money, and may have been offended at the idea of such a large (albeit unlikely) payout. So, an alternate explanation for this negative effect is that anglers may have thrown more brown trout back in protest to the PIT tag bonus assuming they knew which fish were tagged. In theory, the pit tag bonus should work like a lottery in that anglers don't know whether the brown trout they catch are tagged, and therefore worth an additional $300. However, in

Table 15

DID Poisson Regression Results of Rainbow Trout Catch per Trip on the March 2021 Program Kickoff and Subsequent Payment Levers.

	Dependent variable:	
	Rainbow trout catch per trip	
	linear controls	polynomial controls
	(1)	(2)
Post	-0.316^{***}	-0.771^{***}
	(0.077)	(0.130)
Tmt	-0.575^{***}	-0.599^{***}
	(0.026)	(0.026)
Post×Tmt	-0.211^{***}	-0.184^{***}
	(0.032)	(0.034)
Post×Tmt×bonanza	0.032	0.090
	(0.055)	(0.061)
Post×Tmt×3 fish bonus	0.194^{***}	0.126^{**}
	(0.051)	(0.059)
Post×Tmt×pit tag bonus	-0.295^{***}	-0.269^{***}
	(0.055)	(0.059)
Constant	2.105^{***}	2.309^{***}
	(0.090)	(0.113)
Observations	6,360	6,360
Log Likelihood	−24,745.820	−24,377.000
Akaike Inf. Crit.	49,537.640	48,847.990
Note:		*p<0.1; **p<0.05; ***p<0.01
		Standard errors are heteroskedasticity robust.

practice, it is likely that some anglers knew or figured out that tagged fish have their adipose fin clipped. If these anglers were which could have induced them to throw brown trout with intact fins back at a relatively higher rate.

4.6.4 Rainbow Trout Catch-Per-Trip

While the program failed to induce additional brown trout landings, it also did not have a negative impact on the fishery's rainbow trout stock, as catch and retention rates of rainbow trout were largely unaffected. On the whole, the incentivized harvest program decreased average catch per trip for rainbow trout. Table 15 indicates that rainbow trout catch fell by between 17% and 19% when the program kicked-off, and that the introduction of the pit tag bonus in September 2021 augmented the program's base negative effect. The implementation of the three fish bonus for brown trout in August 2021 does appear to have slightly increased rainbow trout catch rates (by between 13% and 21%).

4.6.5 Rainbow Trout Retention Rates

The brown trout harvest incentive also appears to have had a net-negative impact on rainbow trout retention rates amongst unguided boat anglers. Table 16 presents the regression results for two fractional logits of rainbow trout retention rate on treatment levers, while Figure 21 illustrates the average marginal effects of those levers on retention rates as calculated by the two regression models. On average, the program kick-off reduced rainbow trout retention rates by 0.09, while program bonanzas temporarily reversed that negative effect by 0.05. These results may suggest that the representative Lees Ferry angler (and thus, the dominant retention ethic or behavior) was different during bonanza events than at other times.

Table 16

Fractional Logit Regression Results of Rainbow Trout Retention Rate on the March 2021 Program Kickoff and Subsequent Payment Levers.

	Dependent variable:	
	Rainbow trout retention rate	
	linear controls	polynomial controls
	(1)	(2)
Post	-1.340^{***}	-1.325^{***}
	(0.316)	(0.318)
bonanza	0.803^{**}	0.820^{**}
	(0.351)	(0.363)
3 fish bonus	0.655	0.599
	(0.470)	(0.480)
pit tag bonus	0.737^{*}	0.747^{*}
	(0.403)	(0.411)
Constant	0.224	-0.974
	(1.165)	(0.876)
R2	0.025	0.027
Adjusted R2	0.019	0.024
Observations	2,261	2,261

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors are heteroskedasticity robust.

4.7 Discussion

We use my trips, brown trout catch-per-trip, and brown trout retention rate models to simulate daily estimates for trips taken, average brown trout catch per trip, and average retention rates under both no treatment and treatment scenarios for the first

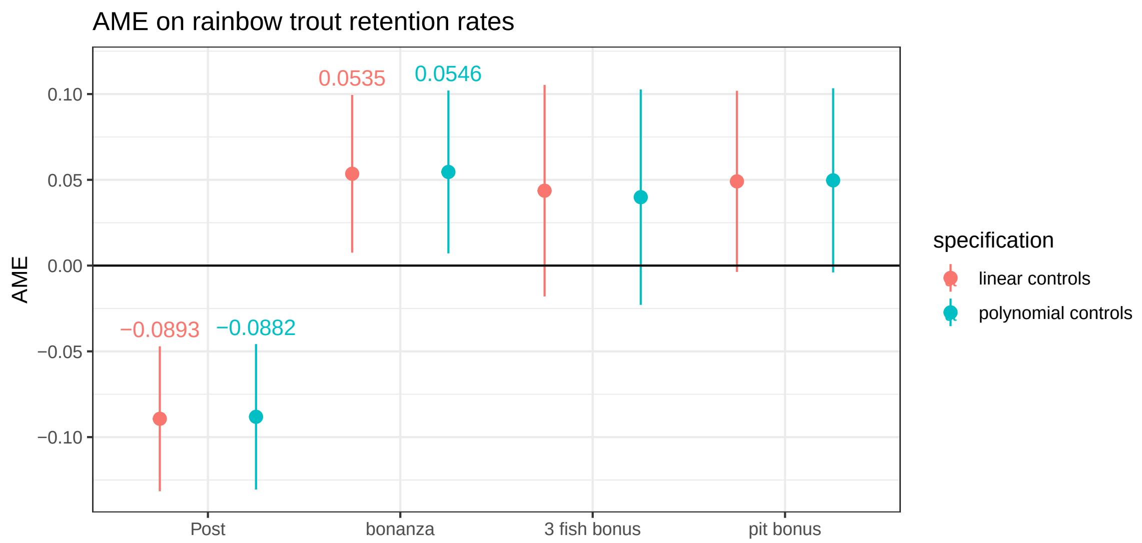

Figure 21. Average Marginal Effects (AME) of Program Treatments on Rainbow Trout Retention Rates. As estimated in the models in Table 16. AMEs which are significant at $p \leq 0.05$ have their estimated means listed.

year of the program (March 1, 2021 - February 28, 2022).[59] My models predict that 284 brown trout were harvested that first year with the treatment levers occurring as they did historically, and that only 196 brown trout would have been harvested that year had the program not been implemented. According to my predictions, the program only induced additional landings of around 88 brown trout over its first year, which is 3.5% of the 2,500 fish goal. The NPS paid $41,529 in rewards over that same time period, meaning that the average bounty paid per additional fish was $472.

For species that are not usually the target of recreational harvest (e.g., Burmese Python in Florida) I might expect the predicted harvest under the no-treatment scenario to be near zero, which would mean most of the observed harvest is additional. That assumption of 100% additionality is less appropriate for species which are recreationally desirable. Given that so few of the brown trout harvested over the

[59]See the Appendix for a discussion of this calculation.

program's first year were additional, Lees Ferry brown trout appear to fall further on the "recreationally desirable" end of the spectrum, which makes this counterfactual estimation approach crucial for understanding the program's impact.

It is important to note that the prediction of 284 brown trout harvested is well below the number of brown trout that were actually turned in for payment during that first year (663). This underestimate is because the Lees Ferry creel, from which I sourced all dependent variables in this study, is a sample of all Lees Ferry anglers, not just those who participate in the harvest incentive program. Therefore, my models provide conditional mean estimations of the *representative* Lees Ferry angler. Over the program's first year, participation shifted from a larger group of anglers retaining one or two brown trout per month to a handful of increasingly proficient anglers. In other words, by the end of year one, program participants were no longer representative of the broader Lees Ferry angler base. This trend of participation converging to a few "career" harvesters is not unique to Lees Ferry; in 2020, 5% of the over 100,000 fish turned in to the Northern Pikeminnow Sport Reward Fishery were caught by a single angler (Pacific States Marine Fisheries Commission, n.d.; Winther et al., 2020). Future research could investigate how program design may drive this consolidation effect, and what that means for program efficacy and cost-effectiveness.

At Lees Ferry, a single angler caught 63 (nearly 10%) of the 663 brown trout turned in during the first program year between January and February 2022. This angler continued participating past my simulation period, and in May 2022 earned nearly $10,000 in reward payments. What is more, I know that this high-performer accesses the fishery via a hiking trail that is difficult to locate and traverse. Because they do not access the fishery at the boat launch, this angler is almost certainly not in the creel data.[60] This top angler also did not begin participating in the program until late December 2021, but has participated every month since, which suggests their harvest may be 100% additional (i.e., they would not have harvested brown trout had the program not induced them to begin fishing at Lees Ferry, to begin targeting brown trout, or to begin retaining brown trout.) In the first six months of 2022, this angler averaged 42.6 brown trout harvested each month. Assuming fishery conditions for year two of the program are similar to what they were in year one and that the top-angler continues harvesting an average of 42.6 brown trout per month (511 per year), I would expect a roughly 280% increase in program-induced brown trout harvests from year one to year two, which emphasizes just how much value one or two highly-effective anglers can bring to a harvest incentive program.[61]

Because the Lees Ferry program appears to have had a negative effect on trip-taking by representative unguided Lees Ferry anglers, any potential additional brown trout landings or incidental rainbow trout landings for that group would have to come from the catch per trip and retention rate margins. The fall in catch rates during the bonanza could be the result of event-activated anglers crowding known brown trout hot spots, startling the fish and preventing some anglers from having sufficient room to cast. Alternately, the bonanzas may have attracted relatively newer Lees Ferry anglers who were less knowledgeable about where or how to catch brown trout while deterring more seasoned Lees Ferry anglers, resulting in lower average catch rates.

[60] We can be fairly certain that there are no other anglers accessing the fishery in this unconventional way who are also significant contributors to program success; if such anglers existed, they would have shown up in the program data cards so I would be aware of them.

[61] We assume another 284 additional brown trout harvested by average Lees Ferry anglers plus the 511 by the most effective angler for a total of 795. 795 is 2.8 times larger than 284.

Model 2 in Table 12 suggests that bonanza events failed to increase daily trips, so the latter hypothesis seems more likely.

Bonanza, derby, or tournament events are a popular method for incentivizing recreational harvest of invasives. Lionfish have been the target of several spearfishing derbies in the past, and Florida augments its ongoing python removal efforts with an annual, 10-day derby. Derbies like those listed have the potential for drumming up interest and bringing in additional effort on the trips and retention rate margins, but—as suggested by my results—may further depress catch rates if their short duration draws in ineffective harvesters who do not return post-event to learn by doing. The Florida Python Challenge faces a similar hurdle, as many challenge participants underestimate how difficult it is to catch or even find pythons, leading them to have low catch rates and to doubt the necessity of removing pythons in the first place (Harvey et al., 2016).

In order to fully capitalize on bonanzas' potential to activate many and new harvesters with strong tastes for retention, event organizers should provide information on where and how to capture the target species in advance of the event. Not only would such an education campaign make these new harvesters more effective, but successful event participants may be more likely to participate in the broader incentivized harvest program going forward.

4.8 Conclusion

From March 1, 2021 through February 28, 2022, fewer than 100 of the 674 brown trout turned in for payment would not have been harvested without the incentivized harvest program's introduction, meaning that over 500 of the fish for which NPS payed rewards were non-additional. This mismatch suggests two things: 1) the program failed to activate additional harvesting effort across all three margins, and 2) many anglers were being overpaid (relative to their minimum willingness-to-accept to supply a brown trout) for fish that they would have harvested anyways.

While the Lees Ferry Incentivized Harvest Program failed to induce additional fishing trips from the average, representative angler, likely due to how remote and costly it is to access the fishery, certain payment levers may well have induced a compositional shift amongst Lees Ferry anglers. Namely, the program seems to have had an unambiguously negative impact on catch per trip for both rainbow and brown trout, which hints that the program may have drawn in new anglers who lacked fishery-specific knowledge on where and how best to target brown trout and were not especially effective at catching rainbow trout. As I found evidence of trip volume falling after the program was implemented, it is likely that the presence of these new anglers (or expectations about crowding) dissuaded some veteran, unguided Lees Ferry anglers from visiting the fishery.

In general, my results point to a possible trade-off between skill or knowledge and angling ethic that may have stymied participation in the Lees Ferry program. Specifically, it appears the program failed to activate existing anglers with the fishery-specific knowledge and experience needed to efficiently target and catch brown trout, while failing to provide sufficient information for newcomers to be effective harvesters.[62] What is more, the lack of additional trips induced by this program suggests that those new anglers may have crowded out the existing, more experienced anglers. In short, harvest incentives that only activate a relatively ineffective group of hunters

[62]NPS launched an instructional video on where and how to catch Lees Ferry brown trout in December 2021, but only 4% of anglers surveyed since have seen the video.

or fishers and fail to provide education or training to those participants are likely to fail. What is more, it may be more cost-effective to invest in a comprehensive education and outreach campaign to not only improve anglers' efficacy at catching the target species, but that also works to lower the willingness-to-accept of otherwise non-activated but high-skill anglers (in Lees Ferry, this is primarily guided anglers) by targeting their intrinsic motivations for either not targeting or releasing members of the target population. The emergence of highly effective "career" bounty hunters in late 2021 suggests that anglers who are motivated by the program and equipped with the knowledge and gear required to catch brown trout can be extremely effective. It is even likely that these anglers could have been activated at lower cost were it more widely known how and where to catch Lees Ferry brown trout, further increasing the potential value of a well-advertised education and outreach campaign.

More work needs to be done in unpacking the relationship between intrinsic motivations (e.g., conservation ethics) and willingness to participate in incentivized harvest programs. Furthermore, it is important to understand where recreational harvesters get their hunting and fishing information in to ensure any education and outreach campaigns are salient. While 78% of anglers surveyed since March 2021 were aware of the Lees Ferry program when planning their trip, it is possible that greater awareness of the program could improve performance either by drawing in potential participants who are unaware of the program or by encouraging anglers planning a trip to come equipped with the right gear for catching and retaining brown trout and with the knowledge of when, where, and how to use it.

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Chapter 5

CONCLUSION

This dissertation highlights the importance of accounting for the full range of feedbacks when managing shared natural infrastructure for nature-based recreation in the Anthropocene. I begin with a broad investigation of the types of social dilemmas (i.e., management challenges defined according to the characteristics of the infrastructures and processes underlying them) that commonly emerge in nature-based recreation systems, as well as a discussion of the portfolio of management interventions available to address those dilemmas. Then I narrow my focus to two case studies that feature different management dilemmas and proposed interventions. In both cases, the proposed interventions are incentive-based, and therefore engineered to address the underlying processes driving their respective dilemmas. I perform evaluations—one *ex ante* and one *ex post*—of both interventions. These program evaluations illustrate the value of data-driven modeling to inform management of recreational systems, and generate useful lessons about the interplay of system context and intervention efficacy for a range of management outcomes.

In Chapter 2, I created a typology of management dilemmas that are characterized as feedbacks or processes within a complex SES. I identified four dilemmas that commonly emerge from recreators accessing (or being unable to access) shared natural infrastructure for nature-based recreation. Then I discussed four additional dilemmas that typically emerge either from those original dilemmas or from management responses to them. These secondary dilemmas are characterized according to the direction in which biomass or—more commonly—information flows between recreators, the environment, and public infrastructure (e.g., rules, norms, monitoring and enforcement capacity, etc.) within a given recreational system.

By comparing numerous case studies, I revealed two key themes in the emergence of these dilemmas: 1) many management dilemmas are correlated with, caused, or amplified by one or multiple margins of recreator heterogeneity; and 2) how visible a dilemma is to system managers determines when and how it gets addressed. Dilemma visibility is jointly determined by monitoring capacity, management mandates, and speed of emergence.

After my broad archetypal analysis of management dilemmas in nature-based recreation, I narrowed my focus in Chapter 3 to perform an *ex ante* evaluation of a prospective management intervention for a "Leave no Trace" dilemma. I found evidence that unbundling the prices of recreational access and use—which, in theory, should more directly target the underlying incentives and processes driving this dilemma—does, in fact, improve management outcomes. This chapter also showcases the value of forward-looking models for designing management interventions in nature-based recreation contexts.

Chapter 4 is an *ex post* evaluation of an incentive-based management intervention aimed at overcoming a "Can't Get There from Here" dilemma in the context of invasive species control. My results suggest that offering incentives for a desired type or amount of recreation may face a range of hurdles, both intuitive and not, that limit their efficacy and cost effectiveness. In particular, I show that incentive programs may be ineffective at inducing the desired behaviors and outcomes if they fail to motivate the most potentially effective resource users (in this case, those fishers with the greatest amount of human infrastructure or knowledge regarding the fishery).

My other contribution from chapter 4 is illustrating the importance of consistent data collection efforts in the uncertain era of the Anthropocene. The COVID-19 pandemic and a multi-year drought both impacted the Lees Ferry fishery during the incentivized harvest pilot program. Consistent data collection efforts by the Arizona Department of Fish and Game, the United States Geological Survey, and many other agencies made it possible for me to disentangle the effect of the pilot program from that of the pandemic, the drought, and other unpredictable and coincident shocks. This study, which relied on the uniquely good data available for the Lees Ferry fishery, would not have been possible in most other recreation systems. The ability to combine high-quality data sources on different system elements (i.e., the resource users, the natural infrastructure, etc.) to account for their interconnected nature will likely be increasingly important in the face of mounting uncertainty and shocks as we progress through the Anthropocene.

The more complex a system, the more uncertainty its managers face. Coupled human-environment systems that host nature-based recreation are characterized by intricate and context-specific processes. Managers with a fuller understanding of the feedbacks that comprise their systems are better equipped to address any dilemmas that may emerge. However, managers of nature-based recreation often face significant resource and objective constraints, both of which contribute to uncertainty.

This dissertation provides an empirically-informed discussion of why it is important that nature-based recreation be managed effectively, and what barriers managers may commonly face. Data-driven modeling will be an important tool for anticipating management dilemmas and for designing effective management interventions for those dilemmas. When it comes to managing these systems, context matters, and often in ways that are difficult to anticipate. More work is needed, therefore, to unpack the nuanced and dynamic interplay of system attributes, management efforts, and outcomes.

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APPENDIX A

CHAPTER 2 APPENDICES

A.1 Recreation Modes and Scopus Search Queries

Table 17

Recreation Modes Included in Scopus Searches and their Affiliated Search Phrases.

Recreation Category	**Recreation Mode**	**Search Query**
Trail Activities	Mountain Biking	mountain AND biking
	Off-roading	OHV OR ORV OR off-road OR offroad OR (off AND road) OR off-highway OR (off AND highway) OR ATV OR all-terrain OR (all AND terrain) OR motorcycle
	Equestrian	horseback OR horse OR equestrian
	Hiking	hiking
Backcountry Activities	Backpacking	backpacking
	Camping	camping
	Foraging	foraging
	Visiting a wilderness or primitive area	wilderness OR primitive AND area
	Rock climbing, Canyoneering	rock climbing OR (rock AND climbing) OR canyoneering
Viewing & Photographing	Viewing or photographing flora or fauna	(bird OR wildlife OR nature) AND (watching OR viewing OR photographing OR photography)
Hunting	Game, waterfowl	hunting
Fishing	Freshwater, saltwater	fishing OR angling OR sport fishing OR (sport AND fishing) OR sport-fishing
Swimming	Lake, river, ocean	swimming
	Snorkeling	snorkel
	Scuba Diving	scuba
	Visiting a beach or waterside	beach OR waterside OR water-side OR riparian

Table 17

Continued from previous page

Recreation Type	**Recreation Mode**	**Search Query**
Boating	Boating	boating
	Sailing	sailing
	Canoeing, kayaking	canoe OR kayak
	Rowing	rowing
	Water/Jet skiing	ski
	Floating/rafting	floating OR rafting
	Sailboarding/ windsurfing	sailboard OR (sail AND board) OR windsurf OR (wind AND surf)
	Surfing	surf
Snow activities	Skiing (downhill, cross-country)	ski
	Snow-shoeing	snowshoe OR (snow AND shoe) OR snow-shoe
	Snowmobiling	snowmobile OR (snow AND mobile) OR snow-mobile

A.2 Case Coding Example

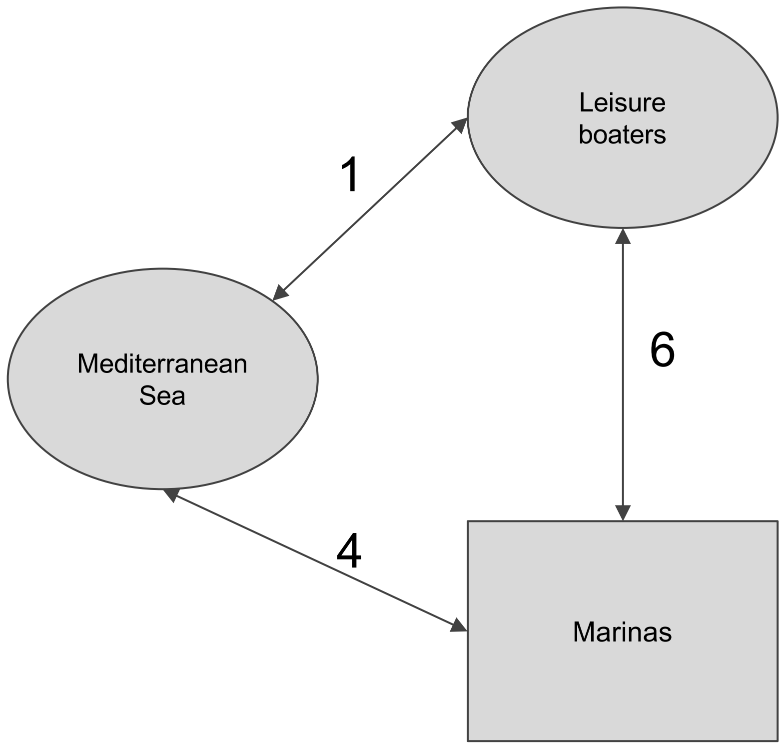

Figure 22. Example of My Case Coding Procedure. Employs the case from Martínez-Laiz et al. (2019).

A.2.1 Labeling the Nodes

RU

Leisure boaters who mostly take short trips a few times a year.

NI

- Local/marina-specific ecosystems within the Mediterranean Sea
- Aquatic invasive species ("potential invaders")

PI

- Marinas on the northern rim of the Mediterranean Sea (HHMI)
- Recommendations re. boat cleaning (SHMI)
- Norms re. following boat cleaning recommendations (SI)
- Predominant belief that individual RUs have a low probability of transporting invasives (HI)

A.2.2 Describing the Dilemmas

Primary Dilemma: $RU \nrightarrow NI$
Can't Get There from Here: Leisure boaters should have better/more access to the Mediterranean Sea. This is implicit in the construction of marinas.

Management Intervention: Build marinas (HHMI)

Secondary Dilemma: $RU \rightarrow PI \rightarrow NI \rightarrow RU$
Clockwise flow of biomass: Boaters *utilize* marinas (**link 6**) to access the sea. The marinas *distribute* boaters and—incidentally—invasive species (**link 4**) around the sea. Accessing the sea *provides U* (**link 1**) for boaters, which keeps them utilizing the marinas to access the sea. Outcome = spread of invasive species.

A.3 Coding Spreadsheet

Table 18

Spreadsheet of Coding Outcomes.

Case	**Exogenous Shocks**	**1st Process**	**1st Outcome**	**Mgmt Intervention**	**2nd Process**	**2nd Outcome**
Pereira et al., 2021	RU: Sudden increased demand for beach visits, infectious disease	HOP	RU risk of harm/ mortality			
Kubo and Shoji, 2016		DPTB	RU risk of harm/ mortality	Close trail segments when bears are sighted	Counter-clockwise: NI $\rightarrow$ PI $\rightarrow$ 1	CGT, degraded RU experience
Burger and Niles, 2014	NI: Sea level rise shrinks beaches	LNT	Disturbed NI			
Weijerman et al., 2018	NI: Climate change damages fish stocks, degrades fish habitat	LNT	Degraded RU experience, degraded NI			

Table 18

Continued from previous page

Case	**Exogenous Shocks**	**1st Process**	**1st Outcome**	**Mgmt Intervention**	**2nd Process**	**2nd Outcome**
Eagleston and Marion, 2017	RU: Evolving camping preferences	LNT	Transformed NI, degraded RU experience			
Chang et al., 2017		LNT	Degraded NI			
Bomanowska et al., 2014	RU: Increasing interest in climbing	CGT	Insufficient access (supply) of recreation opportunities	Install HHMI to enhance access.	Clockwise: RU $\rightarrow$ PI $\rightarrow$ 1	LNT, degraded NI
Hogan et al., 2021	RU: Broader increase in ATV use	LNT	Degraded NI			
Spaul and Heath, 2016		LNT	Disturbed NI			
Shawky et al., 2020	RU: Regional tourism increase	LNT	Disturbed NI			

Table 18

Continued from previous page

Case	**Exogenous Shocks**	**1st Process**	**1st Outcome**	**Mgmt Intervention**	**2nd Process**	**2nd Outcome**
Nguyen et al., 2016		LNT	Degraded NI	Allocate catch shares to First Nation and recreational fishers separately.	Counter-clockwise: NI → PI → RU	HOP, RU risk of harm/ mortality, conflict between user groups
Gstaettner et al., 2017		DPTB	RU risk of harm/ mortality			
K. M. Brown, 2016		HOP	Degraded RU experience, PI transformed		Clockwise: RU → PI → 1	HOP amplified, degraded RU experience
Hughes and Paveglio, 2019	RU: Increase in newcomers/tourists	HOP	RU risk of harm, Conflict between user groups, congestion			

Table 18

Continued from previous page

Case	**Exogenous Shocks**	**1st Process**	**1st Outcome**	**Mgmt Intervention**	**2nd Process**	**2nd Outcome**
McCreary et al., 2019	NI: Climate change creates more frequent and intense weather events	DPTB	RU risk of harm	Provides weather forecasts to help with RU planning.	Counter-clockwise: NI $\rightarrow$ PI $\rightarrow$ RU	CGT, lost RU opportunity (equity)
Höglhammer et al., 2019		CGT	Lost RU opportunity (equity)			
Martínez-Laiz et al., 2019		CGT	Lost RU opportunity	Build marinas	Clockwise: RU $\rightarrow$ PI $\rightarrow$ NI	LNT, spread of IAS
Carello et al., 2018		CGT	Lost RU opportunity	Clip grass and compact snow.	Clockwise: RU $\rightarrow$ PI $\rightarrow$ NI	Degraded NI, spread of IAS

APPENDIX B

CHAPTER 3 APPENDICES

B.1 Permission to Reproduce

This chapter was previously published with co-authors (Jungers et al., 2023). I confirm that all co-authors have granted their permission for this previously published work to be included as a chapter of this dissertation.

B.2 Preparing Extensive Margin Estimation Weights

I use the inverse probability sample weights developed by Abbott et al. (2018) in my extensive margin model estimation, as well as in scaling the extensive margin policy simulations up to the full headboat sector. These weights are products of three inverse probability weights to collectively account for selection along dimensions of survey version, survey non-response, and spatiotemporal variables – thereby producing estimates that are as representative of the population of Gulf of Mexico headboat anglers as possible.

The first component of these estimation weights is the inverse probability that a respondent received the survey version that they did. Anglers in Texas, Alabama, and Northwest Florida encounter more red snapper than gag grouper, so respondents who filled out onboard surveys in those regions received the red snapper version of the follow-up survey with 80% probability and the gag grouper version with 20% probability. Anglers in Southwest Florida encounter relatively more gag grouper, and so received the gag grouper version with 80% probability and the red snapper version with 20% probability. I use only the red snapper surveys, so this first part of the extensive margin weights is 0.80^{-1} for Texas, Alabama, and NW Florida anglers, and 0.20^{-1} for SW Florida anglers.

The second component of the estimation weights control for non-response bias, where non-response is defined as either failing to complete the Internet survey or failing to provide a valid email address on the initial onboard survey. I estimate a logistic regression of survey completion (i.e., whether an individual provided a valid email address on their onboard survey and completed the follow-up survey) on gender, age, income, years of experience an angler has fishing in the GOM, how often an individual goes fishing, and a dummy for home state (Alabama, Florida, Texas, Louisiana/Mississippi, other) to predict the probability that each respondent would have completed the survey. The inverse of these "propensity scores" control for non-response bias based on selection-on-observables assumptions.

The third and final component of the estimation weights are spatial-temporal post-stratification survey weights that ensure the spatial and temporal distribution of the respondents to the onboard survey (after adjusting for survey non-response and survey version) reflects the headboat angler population. Abbott et al. (2018) used logbook data from all Gulf Headboat vessels to account for the percentage of total anglers who took trips during each of the four seasons (January through May, June, July through August, September through December) and four regions (Texas, Alabama, NW Florida, SW Florida) included in the sample. I then use these percentages to compute spatial-temporal post-stratification survey weights – effectively up-weighting responses in space-time cells that are underrepresented in on my sample while down-weighting responses in cells that are overrepresented.

The final weights for the trip choice model are the product of these three components, normalized in the sample.

B.3 Preparing Intensive Margin Estimation Weights

The intensive margin model estimates per-trip demand for red snapper retention for those respondents who chose one of the two trip alternatives in at least one of the fee version choice experiments. Thus, the probability of appearing in the intensive margin estimation sample is the product of the probability of being included in the extensive margin sample (captured by the inverse of the extensive margin estimation weights described above) and the probability of having chosen to take a trip on the fee version choice experiments.

I use the final mixed logit model (Table 9, column 3) to generate estimated probabilities that each individual i would have chosen to take a trip on the fee version choice scenarios. The probability that individual i chooses to take one or the other of the fee version trips is the complement of the probability that they choose the outside (no-trip) option, $Pr(\textit{Opt-out})$. my final intensive margin estimation weights are, therefore, the product of the extensive margin estimation weights (above) and $[1 - Pr(\textit{Opt-out})]^{-1}$. I also estimated the censored Poisson using the extensive margin weights, but it had no notable effect. The estimation results from this alternative weighting are available upon request.

B.4 Estimating Average Marginal Effects and Elasticities

I use the prediction functions from the Apollo package in R to estimate both the average marginal effects (AME) and elasticities for the extensive margin model (Hess & Palma, 2019a, 2019b). The procedures for estimating AMEs and elasticities from a random parameters logit are nearly identical, but I indicate two places where these procedures differ. I use Monte Carlo simulation to consistently estimate these marginal effects and elasticities of the random parameters in my model.

Let X represent a variable whose AME and elasticity I are estimating. For each choice occasion faced by individual i, I first drew 1,000 β_i values and then calculated the corresponding baseline choice probabilities using the original, unaltered data for all variables aside from X. For X, I use the original unaltered data for continuous variables, and set $X = 0$ across all trip alternatives for discrete variables.

I then perturb X in trip alternative one for each choice occasion n and re-estimate the choice probabilities across the same individual and choice-occasion specific 1,000 $beta_i$ draws as used for the baseline choice probabilities. When estimating the AME of a continuous variable, I perturb variable X by adding Δ_c for continuous variables or $\Delta_d = 1$ for discrete variables to each X_n. Δ_c is defined as .001 of the standard deviation of a continuous variable. [63,64]

I estimate both *own* marginal effects and elasticities of alternative-specific attributes (e.g., price, congestion) and *cross* effects on the probability of opting-out (i.e., of choosing the outside option). For demographic variables that only enter the regression through interactions with "optout", I estimate *own* marginal effects and elasticities with the choice to not take a trip, as well as *cross* effects with alternative 1.

In order to estimate the average marginal effects of each observation for each of the 1000 draws for a given alternative, I perform the following calculation for each of the 1000 draws j

$$AME_j = \sum_{n=1}^{2148} \frac{Pr_{nj}^{new} - Pr_{nj}^{baseline}}{\Delta} \tag{B.1}$$

where 2148 is the total number of choice occasions in the sample, n is the choice occasion, j is the draw, and Δ is the amount by which the variable was perturbed.[65] This transformation leaves me with a matrix of AMEs or elasticities by alternative for each of the 1,000 sets of draws. When discussing average marginal effects and elasticities, I describe the distribution of effects across all draws of unobserved heterogeneity.

B.5 Trip-Taking and Aggregate Retention: Policy Simulations

I investigate trip-taking and retention behavior across a grid of trip prices and per-fish retention fees. The trip prices over which I run simulations range from \$0 to \$250 in \$5 increments, while the fees range from \$0 to \$150 in \$5 increments. In order to maintain consistency across estimates, I fix trip-attributes to common values for both trip alternatives across all observations. Congestion is always set to "spacious"

[63] I perturb only the X_n of alternative 1, not that of alternative 2. As a robustness check, I also tried perturbing only alternative 2 attributes, and found only trivial differences in my results, as expected in an unlabelled choice experiment.

[64] When estimating elasticities for a continuous variable, $\Delta_c = 0.01X_{old}$.

[65] When estimating elasticities, Δ is replaced with $0.01 \times Pr_{nj}^{baseline}$.

and the expected catch of fish other than red snapper to eight (the median number of fish other than red snapper actually caught by headboat passengers from 2012-2013).

B.5.1 Extensive Margin: Trip-Taking

B.5.1.1 Simulating the Extensive Margin

I use Apollo's prediction tools to generate a matrix of predicted trip probabilities for each price-fee combination. my extensive margin predictions are drawn from a random parameters logit, so I draw 1,000 predicted probabilities per observation (i.e. choice occasions) and price-fee combination. Some adjustments to the simulation are needed to accommodate for the fact that each simulation concerns a single set of trip attributes vs. the opt-out option, whereas the underlying choice experiments utilize two trip alternatives plus the opt-out. To maintain congruity with my estimation model, I simulate by setting the attributes for alternatives one and two to be always identical. However, this will overstate the probability of the trip alternative and understate the probability of the opt-out without an algebraic adjustment. The necessary adjustment directly follows from the Independence of Irrelevant Alternatives (IIA) assumption, which holds for a given draw of the random preference parameters.

To implement the correction, I extract a matrix of predicted probabilities of opting-out (P_3) for each draw of the random coefficients and price-fee combination, and calculate the true probability of opting-out (P_o) using equation B.2 below.

$$P_o = \frac{2P_3}{1 + P_3} \tag{B.2}$$

The probability of the trip option is then $1 - P_o$. I then store the mean probability of taking the trip over 1,000 random coefficient draws for each individual and price-fee combination in an (N×F×P)×1 "prediction vector," where N is the number of observations, and F and P are the number of fees and prices simulated over.

B.5.1.2 Scaling the Extensive Margin

I use logbook data from GHC vessels in the two years prior to the GHC experiment (2012 and 2013) to create a representative "status-quo" scenario with which to scale each respondent's predicted probability of taking a trip up to total predicted trips aboard Gulf headboat vessels. Of all 2012-2013 headboat trips taken aboard these vessels, I used data from only those 1,850 that occurred within the federal red snapper season (i.e., when red snapper could be retained) and for which I had data on trip price for fishing passengers. I omitted trips for which payment type was "per group" or "no charge," leaving 1,756 trips for which payment type was either "per person" or unspecified. After dropping multi-day and specialty trips (identified through a combination of high trip prices and captain comments), I were left with 1,716 partial or full-day trips.

The trip price for a fishing passenger on those 2012-2013 trips ranged from \$40-\$145, with a mean price of \$83 per head. The mean number of fish other than red snapper caught per angler day is 13, while the median is 8. The long right tail on this distribution has a clear and significant impact on the mean, so I assume 8 fish other than red snapper caught per angler day is more representative of a typical headboat trip. Average red snapper catch per angler trip is distributed normally with a mean of 2.14 fish per angler day. In 2012-2013, the daily bag limit was two red snapper per angler, which implies an average discard of 0.14 red snapper per angler day. The average number of trips (i.e., total angler counts) taken per year between those two years was 39,265.[66]

I plug these status-quo trip attributes into each trip alternative from the bag limit choice experiment scenarios and use the mixed logit model in which price is a random parameter (Table 9, column 3) to estimate predicted probabilities of trip-taking under representative 2012-2013 conditions. I then calculate *scale* such that the weighted mean (weighted with the extensive margin weights from appendix section B.2) of those predicted probabilities times *scale* equals the actual average annual trips taken during the 2012-2013 red snapper seasons (39,265). I multiply *scale* by the (weighted) mean predicted trip probabilities for each fee version simulation to visualize aggregate trip demand for the GHC vessels.

B.5.2 Intensive Margin: Retention Per Angler Day

I estimate the top-censored Poisson model of retention using the post-estimation command *margins* from the *rcpoisson* package in Stata (**rcpoisson**). So that my retention predictions can be consistently multiplied by my extensive margin trip predictions to generate aggregate harvest and revenue predictions, I integrate them over a representative distribution of catch rates from 2012 and 2013 GHC vessel logbook data. For each trip taken, I know the total number of red snapper caught, the number of anglers on board, and trip length. I assign each passenger a catch rate equal to the average number of red snapper caught on their trip, using only trips on which at least one red snapper was caught. For instance, if 12 red snapper were caught on a single trip for which there were six anglers, the data frame from which I

[66] I scale to "trips" rather than to angler-days because the units match my extensive margin model, which pools full- and part-day trips and is thus agnostic about trip-length.

sample catch rates represents this trip as six observations for which two red snapper were caught. I then take N×j (where N=736 equals the the number of observations in my intensive margin estimation and j=100 is the number of draws per observation) draws of catch rate from the full angler population and save those draws in a catch rate matrix.

By integrating over draws of average catch per trip, I assume that catch in excess of the bag limit for high-catch anglers is given to anglers with catch rates below the bag limit, as opposed to discarded. In other words, I implicitly assume that bag limits are enforced at the vessel level, rather than at the individual level. This is consistent with my interviews with headboat captains. I also considered a model of individual accountability under bag limits by fitting an intercept-only negative binomial model to trip-level catch data with number of anglers per-trip included as an exposure variable. I then applied bag limits to angler-specific draws from the catch distribution. However, the unrealistic level of regulatory discards (relative to the headboat survey data) combined with my prior interviews led me to reject this individual bag limit model.

I generate retention predictions over a price-fee grid as in my extensive margin simulations, integrating over 100 draws of catch per observation for each unique combination of price-fee. I then average over these averages for each observation, weighted by the intensive margin weights from appendix section B.3, to provide an expected retention prediction for each pricing bundle. Population-level harvest is the product of predicted trips (scaled to the population as described above) and predicted retention-per-trip at any given price-fee bundle. Expected revenues are calculated for each price-fee combination as the number of predicted trips times the trip price (trip revenues) plus total harvest times the retention fee (fee revenues).

B.6 Ordered Logit of Fee Acceptance on ISCs

This ordered logit model in Table 19 reveals that Gulf residency, whether the collected fees go to the headboat operators or are invested in conservation research (*Vfeetoboat*), if respondents were aware of the GHC pilot program while on their trip (*knew_pilot*), and several indicators of angler avidity (e.g., if a respondent is a member of an angler organization) are not significant determinants of fee acceptance.[67] Instead, only the sociodemographic variables *income*, *age*, and *gender* are significant, with younger, male, and higher income individuals being more likely to support retention fees. my findings hold when the left-hand side variable is replaced with with a binary indicator for "acceptable" (= 1) or for "ambivalent or unacceptable" (= 0).

[67] Of the respondents included in my analysis, 57.17% were aware of the GHC pilot program when they took their recalled fishing trip.

Table 19

Ordered Logit of Fee Acceptance.

	Dependent variable:
	Fee acceptance
	(1)
knew_pilot	-0.448
	(0.254)
gomfishing_years	-0.127
	(0.105)
org_angler	-0.654
	(0.446)
gom_resident	0.155
	(0.300)
age	-0.0166*
	(0.00825)
male	0.708*
	(0.311)
income	0.00465*
	(0.00230)
Vfeetoboat	-0.158
	(0.253)
cut1	-2.058***
	(0.475)
cut2	-1.163*
	(0.478)
cut3	-0.185
	(0.491)
cut4	1.862***
	(0.535)
N	6360
LL	-6067.762
$Pseudo\ R^2$	0.0338

Cluster robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

org_ angler is a binary variable that indicates membership in an angler organization.

APPENDIX C

CHAPTER 4 APPENDICES

C.1 Permission to Reproduce

This chapter is a publishable paper produced with co-authors. I confirm that I am first author on this paper and that all co-authors have granted their permission for this work to be included as a chapter of this dissertation.

C.2 Variables in the ML Predictive Model

Table 20

Full List of Variables and Interactions Included in the ML LASSO Model Used to Predict the log(trips) Counterfactual.

Variables	Coefficient
precip_in:month_2	-1.1340
CAVO:dow_Tuesday	-0.0000
CHAM:dow_Saturday	0.0000
COLM:PETR	0.0000
CORO:TUMA	-0.0000
GUMO:NABR	0.0000
HUTR:month_12	-0.0001
LYJO:dow_Saturday	0.0000
MAPR:month_8	-0.0000
MAPR:dow_Wednesday	-0.0001
NABR:PAAL	0.0000
PAIS:longweekend_1	0.0000
PAAL:wkend_Weekend	0.0000
PETR:v2_trout.fishing	0.0000
PETR:dow_Monday	-0.0000
WABA:wkend_Weekend	0.0000
WABA:dow_Saturday	0.0001
v0_trout.fishing:dow_Saturday	0.0186
month_2:dow_Saturday	-0.5177
month_4:dow_Saturday	0.3446
month_5:dow_Monday	-0.1976
discharge_cfs_mean:discharge_cfs_mean	-0.0000
TUMA:TUMA	-0.0000

Note: Sequences of four capital letters represent monthly recreation visit counts for different National Park Service sites in the Intermountain region.

C.3 Full Model Specifications

Table 21

Full Specification and Outputs of DID Poisson Regression of Brown Trout Catch Per Day.

	Dependent variable:	
	Brown trout catch per trip	
	linear controls	polynomial controls
	(1)	(2)
Post	−0.316	2.704***
	(0.358)	(0.579)
Tmt	0.846***	0.711***
	(0.206)	(0.203)
Post:Tmt	−0.565**	−0.154
	(0.203)	(0.236)
Post:Tmt:bonanza	−0.849***	−1.088***
	(0.216)	(0.241)
Post:Tmt:X3.fish.bonus	−0.122	0.435
	(0.220)	(0.293)
Post:Tmt:pit.tag	0.973	0.264
	(0.222)	(0.258)
spring	−0.562*	−0.726**
	(0.289)	(0.339)
summer	−0.441*	−0.752***
	(0.265)	(0.290)
winter	2.063***	0.740**
	(0.263)	(0.352)
Tmt:spring	1.141***	1.066***
	(0.268)	(0.272)
Tmt:summer	0.880***	0.752***
	(0.253)	(0.256)
Tmt:winter	−1.703***	−1.489***
	(0.246)	(0.254)
year_2019 (base 2022)	0.614***	0.830***
	(0.136)	(0.147)

Table 21
Continued from previous page

	(1) linear controls	(2) polynomial controls
year_2020	0.318*	1.404***
	(0.165)	(0.263)
year_2021	0.931***	−1.572***
	(0.257)	(0.494)
meantemp	0.004	−0.006
	(0.005)	(0.006)
poly(meantemp, 2)2		0.393
		(4.632)
precip_in	−1.331***	−13.918***
	(0.895)	(3.307)
poly(precip_in, 2)2		−56.903***
		(10.971)
watertemp_celsius_mean	−0.016***	−0.042
	(0.036)	(0.047)
poly(watertemp_celsius_mean, 5)2		−10.257**
		(5.059)
poly(watertemp_celsius_mean, 5)3		17.765***
		(4.247)
poly(watertemp_celsius_mean, 5)4		2.162
		(4.240)
poly(watertemp_celsius_mean, 5)5		−9.153***
		(3.296)
discharge_cfs_mean	0.0001	0.0001**
	(0.00003)	(0.00003)
poly(discharge_cfs_mean, 5)2		9.697***
		(2.886)
poly(discharge_cfs_mean, 5)3		1.358
		(2.648)
poly(discharge_cfs_mean, 5)4		0.641
		(2.792)
poly(discharge_cfs_mean, 5)5		−9.971***
		(2.731)
stringency_change_US	−0.059***	−0.335***
	(0.017)	(0.057)
poly(stringency_change_US, 5)2		−58.430***
		(11.536)

Table 21
Continued from previous page

	(1) linear controls	(2) polynomial controls
poly(stringency_change_US, 5)3		-129.744^{***}
		(23.551)
poly(stringency_change_US, 5)4		-217.522^{***}
		(39.116)
poly(stringency_change_US, 5)5		-178.110^{***}
		(32.603)
cases_change_US	0.00000	0.00000^{***}
	(0.00000)	(0.00000)
poly(cases_change_US, 4)2		-17.999^{**}
		(7.315)
poly(cases_change_US, 4)3		-11.808^{**}
		(5.121)
poly(cases_change_US, 4)4		30.367^{***}
		(4.199)
deaths_change_US	0.00003	-0.0001^{***}
	(0.00002)	(0.00003)
poly(deaths_change_US, 4)2		−1.217
		(8.031)
poly(deaths_change_US, 4)3		-28.963^{***}
		(5.293)
poly(deaths_change_US, 4)4		-8.202^{*}
		(4.668)
Constant	-4.488^{***}	-3.135^{***}
	(0.600)	(0.717)
Observations	6,360	6,360
Log Likelihood	−2,946.522	−2,809.435
Akaike Inf. Crit.	5,939.044	5,704.871
Note:		*p<0.1; **p<0.05; ***p<0.01
		Standard errors are heteroskedastic robust.

Table 22

Full Specification and Outputs of Fractional Logit Regression of Brown Trout Retention Rate.

	Dependent variable:	
	Brown trout retention rate	
	linear controls	polynomial controls
	(1)	(2)
Post	0.256	−0.171
	(0.443)	(0.454)
bonanza	−0.785	−0.315
	(0.627)	(0.664)
3 fish bonus	2.323***	2.601***
	(0.721)	(0.758)
pit tag bonus	−1.941***	−2.102***
	(0.726)	(0.760)
Weekend	0.042	0.125
	(0.325)	(0.337)
spring	0.234	0.491
	(0.582)	(0.626)
summer	−0.549	−0.442
	(0.535)	(0.555)
winter	0.478	1.513
	(0.859)	(0.932)
meantemp	0.007	0.034*
	(0.018)	(0.019)
precip_in	6.652*	3.469
	(3.887)	(2.227)
poly(precip_in, 3)2		0.179
		(2.274)
poly(precip_in, 3)3		−2.032
		(2.326)
watertemp_celsius_mean	−0.002	−0.044
	(0.112)	(0.116)
discharge_cfs_mean	−0.0003**	−19.469***
	(0.0001)	(7.131)
poly(discharge_cfs_mean, 3)2		−4.095
		(7.236)

Table 22
Continued from previous page

	(1) linear controls	(2) polynomial controls
poly(discharge_cfs_mean, 3)3		-20.462^{***}
		(7.585)
Constant	1.459	-2.859
	(2.136)	(1.976)
R2	0.156	0.208
Adjusted R2	0.118	0.16
Observations	301	301

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors are heteroskedastic robust.

Table 23

Full Specification and Outputs of DID Poisson Regression of Rainbow Trout Catch per Day.

	Dependent variable:	
	Rainbow trout catch per trip	
	linear controls	polynomial controls
	(1)	(2)
Post	-0.316^{***}	-0.771^{***}
	(0.077)	(0.130)
Tmt	-0.575^{***}	-0.599^{***}
	(0.026)	(0.026)
Post:Tmt	-0.211^{***}	-0.184^{***}
	(0.032)	(0.034)
Post:Tmt:bonanza	0.032	0.090
	(0.055)	(0.061)
Post:Tmt:X3.fish.bonus	0.194	0.126^{**}
	(0.051)	(0.059)
Post:Tmt:pit.tag	-0.295	-0.269^{***}
	(0.055)	(0.059)
spring	0.101^{***}	0.120^{***}
	(0.033)	(0.043)
summer	0.067^{**}	0.117^{***}
	(0.029)	(0.036)
winter	-0.259^{***}	-0.146^{**}
	(0.046)	(0.058)
Tmt:spring	-0.421^{***}	-0.398^{***}
	(0.037)	(0.038)
Tmt:summer	0.045	0.062^{*}
	(0.034)	(0.034)
Tmt:winter	0.317^{***}	0.339^{***}
	(0.051)	(0.052)
year_2019 (base 2022)	0.026	-0.002
	(0.019)	(0.021)
year_2020	-0.347^{***}	-0.467^{***}
	(0.027)	(0.060)
year_2021	0.035	0.307^{***}
	(0.069)	(0.105)

Table 23
Continued from previous page

	(1) linear controls	(2) polynomial controls
meantemp	0.004	0.003***
	(0.001)	(0.001)
poly(meantemp, 5)2		−2.329***
		(0.848)
poly(meantemp, 5)3		4.266***
		(0.585)
poly(meantemp, 5)4		−3.733***
		(0.584)
poly(meantemp, 5)5		2.323***
		(0.619)
precip_in	0.126***	−0.239**
	(0.103)	(0.110)
poly(precip_in, 2)1		
poly(precip_in, 2)2		6.584***
		(0.414)
watertemp_celsius_mean	−0.009***	−0.006
	(0.006)	(0.007)
poly(watertemp_celsius_mean, 4)2		0.541
		(0.892)
poly(watertemp_celsius_mean, 4)3		0.431
		(0.716)
poly(watertemp_celsius_mean, 4)4		2.179***
		(0.664)
discharge_cfs_mean	−0.00002	−0.00002***
	(0.00000)	(0.00001)
poly(discharge_cfs_mean, 5)2		0.708
		(0.507)
poly(discharge_cfs_mean, 5)3		−0.385
		(0.483)
poly(discharge_cfs_mean, 5)4		−0.697
		(0.438)
poly(discharge_cfs_mean, 5)5		−3.531***
		(0.439)
stringency_change_US	0.014***	0.017***
	(0.002)	(0.003)

Table 23
Continued from previous page

	(1) linear controls	(2) polynomial controls
poly(stringency_change_US, 5)2		-5.383^{***}
		(0.671)
poly(stringency_change_US, 5)3		-5.106^{***}
		(1.046)
poly(stringency_change_US, 5)4		-3.581^{***}
		(1.246)
poly(stringency_change_US, 5)5		-3.316^{***}
		(1.163)
cases_change_US	-0.00000	-0.00000^{***}
	(0.00000)	(0.00000)
poly(cases_change_US, 5)2		-1.686
		(1.393)
poly(cases_change_US, 5)3		9.820^{***}
		(1.210)
poly(cases_change_US, 5)4		-5.347^{***}
		(0.965)
poly(cases_change_US, 5)5		-2.707^{***}
		(0.882)
deaths_change_US	0.00002	0.00001
	(0.00000)	(0.00001)
poly(deaths_change_US, 5)2		4.145^{**}
		(1.811)
poly(deaths_change_US, 5)3		3.585^{***}
		(1.258)
poly(deaths_change_US, 5)4		2.931^{***}
		(0.928)
poly(deaths_change_US, 5)5		2.984^{***}
		(0.921)
Constant	2.105^{***}	2.309^{***}
	(0.090)	(0.113)
Observations	6,360	6,360
Log Likelihood	$-24{,}745.820$	$-24{,}377.000$
Akaike Inf. Crit.	49,537.640	48,847.990

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors are heteroskedastic robust.

Table 24

Full Specification and Outputs of Fractional Logit Regression of Rainbow Trout Retention Rate.

	Dependent variable:	
	Rainbow trout retention rate	
	linear controls	polynomial controls
	(1)	(2)
Post	-1.340^{***}	-1.325^{***}
	(0.316)	(0.318)
bonanza	0.803^{**}	0.820^{**}
	(0.351)	(0.363)
3 fish bonus	0.655	0.599
	(0.470)	(0.480)
pit tag bonus	0.737^{*}	0.747^{*}
	(0.403)	(0.411)
Weekend	−0.185	−0.169
	(0.191)	(0.195)
spring	−0.254	−0.299
	(0.346)	(0.356)
summer	0.088	0.276
	(0.331)	(0.372)
winter	−0.354	−0.201
	(0.441)	(0.460)
meantemp		−3.568
		(7.311)
poly(meantemp, 3)2		−6.985
		(5.452)
poly(meantemp, 3)3		2.649
		(4.044)
precip_in		−4.527
		(4.495)
poly(precip_in, 2)2		5.679
		(5.136)
watertemp_celsius_mean	-0.115^{*}	-0.120^{*}
	(0.066)	(0.066)
discharge_cfs_mean		−6.183
		(5.438)

Table 24
Continued from previous page

	(1) linear controls	(2) polynomial controls
poly(discharge_cfs_mean, 2)2		0.421
		(4.135)
Constant	0.224	−0.974
	(1.165)	(0.876)
R2	0.025	0.027
Adjusted R2	0.019	0.019
Observations	2,261	2,261
Note:		*p<0.1; **p<0.05; ***p<0.01
		Standard errors are heteroskedastic robust.

C.4 Procedure to Calculate Brown Trout Landings

I use a panel of controls and models of daily trip demand (model 1 of Table 12), catch-per-trip (model 1 of Table 13), and retention rate (model 1 of Table 14) to predict daily values for each of those three margins over the first year of the program (March 1, 2021 - February 28, 2022) under *treatment* and *no treatment* scenarios.[68] For the *treatment* scenario, the program design levers turn on for any given day t as they actually did over the course of that first program year. In contrast, the design levers stay switched off across all of the *no treatment* predictions. I calculate daily brown trout landings as

$$landings_{tj} = trips_{tj} \times catch\ per\ trip_{tj} \times retention\ rate_{tj} \tag{C.1}$$

where $j = 0$ for predictions under the *no treatment* scenario, and $j = 1$ for predictions under the *treatment* scenario. For any given day, additional landings are

$$additional\ landings_t = landings_{t1} - landings_{t0} \tag{C.2}$$

[68]This controls panel was missing data for mean water temperature on July 22, 2021. The mean water temperature on both the day prior and day following was 12.7 degrees C, so I use that same value for my catch and retention predictions.

Finally, I sum additional daily landings over all 365 days to get additional annual landings.

$$additional\ annual\ landings = \sum_{t=1}^{365} additional\ landings_t \tag{C.3}$$

I use only the linear models for catch and retention when running these predictions. The polynomial models, while allowing for more flexible incorporation of controls, result in spurious catch estimates that carry through the estimation procedure to landings.

Model 1 in Table 12 has log(trips) as its dependent variable, so I must transform the daily log(trips) estimates from that model into daily trips estimates before I can perform the above calculations. To do so, I use a smearing estimate procedure from Duan (1983) as described by Wooldridge (2016).

If I assume that the trip DID model's residuals u are independent of the explanatory variables, then

$$\widehat{trips}_{tj} = \hat{\alpha}_0 exp(\widehat{log(trips)}_{tj}) \tag{C.4}$$

is a consistent estimate of daily trips, where $\hat{\alpha}_0$ is the conditional mean of the model's residuals, or

$$\hat{\alpha}_0 = n^{-1} \sum_{i=1}^{n} exp(\hat{u}_i) \tag{C.5}$$