OBSERVABILITY AND STAKEHOLDER CONFLICT IN RESOURCES MANAGEMENT

ABSTRACT. Heuristic learning from personal experience is hard-wired in humans, but overreliance on experiential samples may lead to biased beliefs when such samples are not representative of the population. Prominent examples include skepticism towards climate change and an increasingly vocal anti-vaccine movement. In turn, biased beliefs may lead to stakeholder conflict when different parties hold competing views of reality and financial stakes are high. In this paper we focus on the commercial fishing industry. We develop a theoretical model to study harvesters' incentives to challenge the science that informs management when the claims of official science are at odds with their personal experience. In the empirical application, the case of the Georges Bank cod fishery, we estimate the distribution of extra profits industry would expect to earn if their view of science were incorporated into policy. Our findings show strong incentives to lobby for lax regulations even when harvesters hold relatively low confidence in their own beliefs. An impatient industry would have strong incentives to challenge the official science. While the stock would eventually collapse in this scenario, leading to welfare losses, the crash of the cod population would take time. The industry's overreliance on first-hand observations will ultimately undermine its own interests. This paper highlights the importance of effectively communicating and translating the technical aspects of science to the relevant audiences, particularly those directly impacted by its use in policy.

JEL: D82, Q20, Q22, Q28

Keywords: bounded rationality, conflict, heuristic learning, information, marine policy

1. INTRODUCTION

Personal experience plays a central role in how humans understand the world (Kolb 1984). A growing body of work suggests that biased perceptions drawn from personal experience dominate even in the face of overwhelming scientific evidence to the contrary. This phenomenon has been ascribed to the fact that processing statistical information is cognitively demanding,

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whereas heuristic learning from personal experience is hard-wired into humans to be automatic and immediate (Barron and Erev 2005; Weber 2010). The divergence in cognitive cost leads individuals to rely heavily on personal experience when interpreting information, an issue which can be understood through the lens of bounded rationality (Lipman 1995, Conlisk 1996, Rubinstein 1998, Kahneman 2003, Viale 2020). The role of samples in experiential learning has inspired the metaphor of the *naive intuitive statistician* (Fiedler and Juslin 2006, Juslin, Winman and Hanson 2007, Elwin 2013). Under this view, an agent is an "intuitive statistician" in his ability to accurately describe the properties of the experienced sample, but "naively" interprets that sample as representative of the whole population. Thus, unable to recognize and adjust for the biased experience, the non-representativeness of the sample is translated into biased beliefs. According to Elwin (2013), "…even though the experienced sample is often systematically biased because it is contingent on the individual's own actions, the mind cannot adjust for the process by which the sample was produced" (p. 327). Fiedler refers to this phenomenon as "meta-cognitive myopia" (Fiedler 2000, Fiedler 2008). The dominant role personal experience has in shaping perception is highlighted by a 2019 Pew poll that estimated that only 60% of Americans think scientists should play an active role in policy debates on scientific issues, and 55% feel that scientists are no better, or worse, than the general public at making decisions on scientific issues (Pew Research Center 2019). Likewise, according to an ABC poll, only 32% of Americans "…trust the things scientists say about the environment completely or a lot" (ABC News 2006).

In this paper we contribute to the literature on the political economy of renewable resource extraction (Johnson and Libecap 1982, Karpoff 1987, Turner and Weninger 2005). Concretely, we explore the bias towards personal experience as a key force driving conflict between industry and regulators of marine resources. The idea that biased perceptions may drive this conflict has been suggested in both the popular press (see, e.g. Cook and Daley 2003, Bergman 2020) and the academic literature (Neis et al. 1999, Harms and Sylvia 2001, Dobbs 2000, Anuchiracheeva, Shivakoti and K. 2003, Miller et al. 2004, Hartley and Robertson 2006, Boström 2006, Johnson and van Densen 2007, Johnson 2007, Wendt and Star 2009, DeCelles et al. 2017, Levin et al. 2020). To illustrate, there has been a longstanding disagreement between fishermen and scientists on the status of cod stocks in the Gulf of Maine. Dr. Micah Dean of the Massachusetts Division of Marine Fisheries states that "Many of our fishermen…have a difficult time believing the scientific perspective on the cod stock…But there are good reasons why fishermen have this perspective. Regulations shape the way fishermen see the cod population" (Bergman 2020). In another example, this time on haddock, "…numerous fishers said the [stock] assessment doesn't match what they're seeing on the water, where haddock appear to them to be plentiful.…We seem to find plenty, but they [scientists] can't" (Whittle 2023). Or, "…we fishermen cover far more water than does NOAA [National Oceanic and Atmospheric Administration]. We fish hundreds of miles of marine habitat each voyage. Thus, we have the best sense of fish stocks" (Leeman 2023). "You [NOAA]'ll damn the seaboard on 1/12 of 1% knowledge when the entire fishing fleet is seeing no problem with the species rebuilding process" (Leeman 2022). In fact, only 7% of fishermen surveyed in the Northeast Multispecies fishery felt that the science supporting fisheries management decisions is accurate, while 29% disagreed and 61% strongly disagreed (Holland, Pinto da Silva and Wiersma 2010).

Minimum mesh sizes such as those employed in the Gulf of Maine and Georges Bank are specifically designed to left-truncate catch distributions and area closures keep fishermen away from spawning fish. These input controls mean fishermen fail to receive signals over two critical components of the population that play key roles in the future, not current, productivity of the stock: juveniles and the number of spawning adults. In other words, different policy instruments determine how biased the sample that fishermen observed is, and thereby how biased their learning is regarding recruitment (i.e., number of new young individuals that enter the population in a given year). In turn, the fact that commercial fishermen exhibit extremely high self-trust on their knowledge on fisheries management −above that of other stakeholders− (Eggert, Kataria and Lampi 2016) contributes to the conflict with regulators. In fact, it is not uncommon for the fishing industry to contract its own scientific consultants to contest the findings of government scientists and to hire lobbyists to challenge regulations (Rosenberg 2003). Indeed, lobbying is far from rare in this industry. Examples include industry groups lobbying for higher fishing quotas in Europe (Corporate Europe Observatory 2017), seeking access to closed areas in the U.S. Mid-Atlantic region (Repetto 2001), or watering down groundfish regulations in Alaska (Federman 2023). Similarly, the recently created New England Fishermen Stewardship Association, an industry advocacy group, "is leading the charge against…overregulation and wind-turbine development in the Gulf of Maine" (Zymeri 2023). Conflict is not uncommon in other sectors of the economy, but what sets commercial fishing apart is the possibility of regulatory capture, long observed in this industry (Peña Torres 1997, Costello and Grainger 2018). If, motivated by biased beliefs on stock productivity and distrust of management, the industry is successful in challenging scientific advice, over-harvesting and welfare loss may follow.

Despite this longstanding and widespread recognition, there has been no formal economic investigation of the implications that biased perceptions may have for marine policy. This in spite of the economic profession's recognition of the important role personal experience plays in shaping individuals' attitudes towards redistributive policies such as tax reforms (Piketty 1995). In this paper, we develop a theoretical model of the feedback between fisheries management instruments and harvesters' experiential perceptions on stock productivity (as shaped by the samples harvesters observe while fishing), with an eye towards industry lobbying incentives around management measures. We show that when management policies can differentially impact fishermen's perceptions, they have the potential to undermine the perceived validity of conservation measures and increase conflict with the scientific advice. To quote David Goethel, Hampton fisherman and former member of the New England Fishery Management Council, "It's almost been handed down from fathers to sons that you can't trust the scientists. . . They need to spend more time on the back decks of boats. . . They are looking at building more elegant computer models and I want them to spend more time at sea" (Cresta 2012). Our objective in this paper is to highlight the management implications of this wedge in beliefs on resource productivity between the regulator and the regulated industry. By doing so we highlight the novel proposition that when setting regulations, managers should consider the feedback between regulations and the beliefs of regulated entities, and thus ultimately the incentives to lobby against management.

We use an empirical case study, cod on Georges Bank, to explore the incentives that can be generated under biased perceptions of stock status, driven by fishermen's daily observations, and shed light on how understanding these incentives can assist management decision-making. Notably, our analysis relies on a real-world stock assessment of cod in Georges Bank, rather than on a simplified representation of the biology of the stock, i.e., Gordon-Schaefer model, as is commonly the case in economic applications.[1] Specifically, we simulate projections under three possible scenarios: (i) actual regulators' assessment with current limits staying in place, (ii) alternate state of the world using fishermen's perspective on the cod population and relaxed regulations, and (iii) actual regulators' assessment of cod population with fishermen's preferred relaxation of harvest limits. Our findings confirm strong economic incentives for the industry to challenge the official science in order to increase harvest quotas, even at low levels of impatience (discount rate) and confidence in their own observations. We demonstrate how upward-biased beliefs on stock abundance can easily lead to resource depletion and welfare losses over time. Our results highlight the importance of effectively communicating the official science to the relevant stakeholders, especially those directly impacted by its use in policy, and the potential benefits of cooperative research (e.g., industry-led population surveys) in fostering mutual understanding and trust between scientists and industry.

2. The Model

The industry harvests a fishery resource. A regulator manages the resource in order to limit fishing mortality by setting an aggregate catch limit, Q, each season. This catch limit is enforced with a set of management policies (e.g. effort limits, gear restrictions, area closures), compactly denoted by vector $\boldsymbol{\theta} \in \Theta$, which determines how the industry "samples" the fish population while harvesting the resource. Thus, each alternative vector of policy instruments in Θ will determine the extent to which the industry is able to infer the true parameter values describing the productivity of the fish stock. As discussed below, we allow for the possibility that the information contained in the sample observed by the industry may be incomplete and induce biased beliefs on recruitment. In our setting, as in most real-world commercial fisheries, the regulator selects $\boldsymbol{\theta}$ to ensure that aggregate harvest does not exceed Q, but is otherwise unaware of the informational role $\boldsymbol{\theta}$ plays in shaping industry's beliefs. In other words, the regulator does not purposely select $\boldsymbol{\theta}$ to align industry beliefs with the findings of official science. Our

[1] A stock assessment "is the scientific process of collecting, analyzing, and reporting on the condition of a fish stock and estimating its sustainable yield. Stock assessments are the backbone of sustainable fisheries management" . For details, see `https://www.fisheries.noaa.gov/insight/stock-assessment-model-descriptions#stock-assessment-models`.

objective is to show how disparity in beliefs between the regulator and industry may undermine resource management.

Let $\Pi(y, s)$ denote industry profits, where y is harvest and s stock biomass. We assume that Π is increasing and concave in both arguments, with $\Pi_{ys} > 0$. Without loss of generality, in what follows we specify a two-period model in which the industry is assumed to display foresight and maximize expected profits over the two seasons.[2] Harvesters attempt to maximize the two-season profits given the current status of the stock and the regulations in place to enforce the catch limits. Thus, firms solve the following program

$$\begin{aligned} &\max_{y_1, a\in\{0,1\}} \left[\Pi(y_1, s_1) - a\psi\right] + \beta V_2(s_2; a) \\ &s.t. \quad s_2 = R(s_1 - y_1|\eta) \text{ where } \eta \sim G(x|\rho, \boldsymbol{\theta}) \\ &\qquad\quad y_1 \leq Q_1 \end{aligned} \tag{1}$$

where $a \in \{0, 1\}$ denotes a costly action by the industry that, if undertaken in the first period, increases the catch limit in period 2. What we have in mind here is that the industry has the option to lobby the regulators before period 2 starts in order to increase that season's quota to $Q_2 + \Lambda$, with $\Lambda > 0$.[3] The cost of action a is given by $c(a) = a\psi$, where ψ is a positive constant. Note that if this increased quota is indeed adopted by the regulator, it will be enforced with the set of policies $\boldsymbol{\theta'}$, which may or may not be equal to the original regulations. In program (1), η represents the state of the fishery environment in period 1, a random variable distributed

[2] Assuming a longer time horizon would not change our results but add notation. Moreover, while fishermen exhibit heterogeneity in their attitudes towards the economic and biological tradeoffs associated with the harvest of fish stocks, most favor short-term profit considerations (see, for example, Harms and Sylvia 2001).

[3] Under the US federal fishery management system, the industry may, for example, hire consultants to be part of the Advisory Panel that provides information relevant to the Stock Assessment Review process and Scientific and Statistical Committee process in setting the Acceptable Biological Catch, the upper bound for the annual catch limits that must be set by the regional Fishery Management Councils. The industry may also attempt to influence the quota setting process at the Council level, by limiting the precautionary quota buffers for management uncertainty. Of note is that regulations, including quotas, are set prior to the start of the fishing season in the vast majority of fisheries (see, e.g. `https://www.fisheries.noaa.gov/new-england-mid-atlantic/commercial-fishing/sector-management-northeast-multispecies-fishery#annual-catch-entitlements`).

on $[\underline{\eta}, \bar{\eta}]$ according to the cumulative distribution function F, and where R denotes the stock-recruitment relationship, which is assumed increasing in η and increasing and concave in residual stock (escapement) $z = s - y$ for all η. We assume this function F is known by the manager since the manager has access to both fishery independent and fishery dependent data.[4] On the other hand, the industry assesses η based on two informational channels: (i) the data available to harvesters, as given by the observed sample under policy instruments $\boldsymbol{\theta}$, which determines beliefs $\mu(\cdot|\boldsymbol{\theta})$; and, (ii) the claims of the manager regarding the distribution of η, F. We allow for the possibility that the industry puts only partial weight on the evidence provided by managers. This could be due, for example, to the industry's mistrust towards the regulator and official science (Hartley and Robertson 2011, Johnson and McCay 2012, Ford and Stewart 2021), and to confirmation bias leading to harvesters' overconfidence on their ability to assess the stock via personal experience (Rabin and Schrag 1999, Kraak et al. 2014, Eggert, Kataria and Lampi 2016, Dean et al. 2023). Consequently, the industry beliefs on η are given by the following finite mixture distribution

$$G(\cdot|\rho, \boldsymbol{\theta}) = \rho\mu(\cdot|\boldsymbol{\theta}) + (1-\rho)F \tag{2}$$

where the mixing parameter ρ can be seen as the industry's degree of mistrust towards the regulator (or, alternatively, as industry's confidence on their own observations on the stock). We say that the industry operates under full information when $G(\cdot|\rho, \boldsymbol{\theta}) = F(\cdot)$, which only occurs when $\rho = 0$ (i.e., complete trust on the regulator) or when the policies $\boldsymbol{\theta}$ allow the industry to gather unbiased information on η, that is, when $\mu(\cdot|\boldsymbol{\theta}) = F$. Thus, our model accommodates two types of frictions preventing the industry from knowing the true state of the stock, namely, overreliance on personal experience and nonrepresentative samples, and misgivings towards management and the official science used to inform policy. The larger $\rho \in [0, 1]$, the less reliant beliefs are on third-party information.

[4] The assumption that the regulator knows F is adopted for convenience and is not critical for our results. We could have alternatively assumed that the regular observes F with noise, but that would have only added notation. It is the misalignment between the industry's and the regulator's beliefs that matters for our purposes.

In eq. (1), $V_2(s_2, a)$ is defined as follows

$$V_2(s_2;0) = \max_{y_2} E\Pi(y_2, s_2) \quad \text{s.t.} \quad y_2 \leq Q_2 \tag{3}$$
$$= \max_{y_2} \int \Pi\left(y_2, R(s_1 - y_1|u)\right) dG(u|\rho, \boldsymbol{\theta}) \quad \text{s.t.} \quad y_2 \leq Q_2$$

when the industry does not lobby the regulator, i.e., $a = 0$. Thus, $V_2(s_2; 0)$ represents the maximized expected profits in period 2 under status quo catch limit Q_2 and beliefs $G(\cdot|\rho, \boldsymbol{\theta})$. Conversely, if the industry undertakes lobbying activities to influence the regulator, we have

$$V_2(s_2;1) = \max_{y_2} E\Pi(y_2, s_2) \quad \text{s.t.} \quad y_2 \leq Q_2 + \Lambda \tag{4}$$
$$= \max_{y_2} \int \Pi\left(y_2, R(s_1 - y_1|u)\right) dG(u|\rho, \boldsymbol{\theta}) \quad \text{s.t.} \quad y_2 \leq Q_2 + \Lambda$$

Since we are interested in the incentives that binding quotas create for the industry to contest the official science, in what follows we assume that the industry expects the harvest limits in both periods to bind, i.e., $Q_1 < y_1^*$ and $Q_2 < y_2^* \leq Q_2 + \Lambda$.[5] Thus, from (3) and (4) it is immediate that the industry will engage in costly lobbying if the following condition holds

$$\beta \int \left[\Pi(y_2^*, R(s_1 - Q_1|u)) - \Pi(Q_2, R(s_1 - Q_1|u))\right] dG(u|\rho, \boldsymbol{\theta}) > \psi \tag{5}$$

According to (5), only if it pays for the industry to spend amount ψ lobbying to increase the catch limit in season 2, will the industry find it optimal to undertake the costly action a in period 1. This will occur when beliefs $G(\cdot|\rho, \boldsymbol{\theta})$ lead the industry to expect (i) the catch limit Q_2 to bind; and (ii) that the discounted incremental expected profit associated with an increased catch limit $Q_2 + \Lambda$ will be larger than the cost ψ. This is intuitive since only when industry is led to believe that their optimal catch will be constrained by the proposed quotas will they have incentives to engage in lobbying. In addition, they will only do so if the return from lobbying is positive. Note that conditions (i) and (ii) depend on both $\boldsymbol{\theta}$, the vector of regulations in place to enforce catch limits, and on ρ, the degree of industry's distrust towards the regulator-provided information. Thus, our specification allows for industry to exhibit upward or downward beliefs

[5] If the unconstrained harvest optimum in 2 is higher than the increased quota, $y_2^* > Q_2 + \Lambda$, then condition in (4) must hold for the constrained optimum $y_2^c = Q_2 + \Lambda$ rather than y_2^*.

about the growth potential of the fish population depending on how quotas are enforced, and on the historical frictions between firms and management.

For concreteness, assume first that the industry operates under full information, $G(\cdot|\rho, \boldsymbol{\theta}) = F$. In this case, as long as the manager sets policy taking into account the interests of the industry, the optimal catch in period 2 will not exceed Q_2 and inequality (5) will not be satisfied. Thus, industry lobbying will not take place. Conversely, assume, as it is typically the case, that $(\rho, \boldsymbol{\theta})$ lead the industry to overestimate s_2 (Whittle 2023). This is consistent with the multiple testimonies by industry members quoted earlier, with the fact that fishermen oversample the areas where fish are likely to aggregate (i.e., fishermen *target* the catch), and with confirmation bias whereby new evidence is interpreted as supporting industry's beliefs on abundant stocks. Overestimation of the stock would occur if, for example, $G(\cdot|\rho, \boldsymbol{\theta})$ first-order stochastically dominates F.[6] This later condition would make (5) more likely to hold for any cost level ψ. In this case, and contrary to the industry's beliefs, the stock is less productive than expected and the optimum harvest under perfect information may be unconstrained by the original quota limit, $\text{argmax}_{y_2}\ E\Pi(y_2, s_2; F) \leq Q_2 < y_2^*$.[7] As a result, the industry would engage in wasteful spending of ψ on lobbying in return for an increase in the original catch limit Q_2, which is not expected to bind under full information. Moreover, if harvesters must commit inputs for the entire season before the fishing actually starts, overestimation of stock biomass may lead to misallocation of effort, higher costs and lower expected profits than would be otherwise optimal. On the other hand, as the industry learns to trust the official science, the incentives to lobby management identified earlier will eventually vanish.

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[6] G first-order stochastically dominates F, denoted $G \succeq_{FSD} F$, if $G(x) \leq F(x)$ for all x, with strict inequality at some x. To verify that this condition on beliefs implies overestimation of s_2 by harvesters, write the difference in mean biomass as $E[s_2, G)] - E[s_2, F] = \int R(s_1 - y_1|u)[g(u|\rho, \boldsymbol{\theta}) - f(u)]du$. Integrating by parts, we obtain $E[s_2, G)] - E[s_2, F] = -\int \left(\frac{\partial R(s_1 - y_1|u)}{\partial u}\right)[G(u|\rho, \boldsymbol{\theta}) - F(u)du] \geq 0$, where the last inequality follows from $\left(\frac{\partial R(s_1 - y_1|u)}{\partial u}\right) \geq 0$ and $G(\cdot|\rho, \boldsymbol{\theta}) \succeq_{FSD} F$.

[7] If $G \succeq_{FSD} F \implies y_2^* > \text{argmax}_{y_2}\ E\Pi(y_2, s_2; F)$. Indeed, note that $\int \Pi_y[g(u|\rho, \boldsymbol{\theta}) - f(u)]du = -\int \Pi_{ys} R_\eta [G(u|\rho, \boldsymbol{\theta}) - F(u)]du > 0$ for all y, where the equality is obtained by integrating by parts, and the inequality follows from first-order stochastic dominance and $\Pi_{ys}, R_\eta \geq 0$. Thus, the unconstrained optimum harvest under beliefs $G(\cdot|\rho, \boldsymbol{\theta})$ will be higher than that under F.

While we have referred to the "industry" as the relevant unit of analysis throughout this section for exposition purposes, in a catch share fishery condition (5) needs only hold for a subset or coalition of harvesters willing to afford the lobbying cost necessary to increase the industry's catch limit in the next period. Examples of such coalitions include cooperatives or sectors that ensure coordination of the activities of their members, firms that own fleets of vessels, or informal cliques of cooperative fishermen. If it pays for a given coalition to invest ψ to increase its quota in the following period, the coalition will do so thereby benefiting the rest of harvesters by providing a club good of sorts (i.e. by effectively subsidizing the contribution of others, who will in turn expect to benefit from higher quotas). This follows from condition (5) by substituting the industry landings and catch limit by the coalition's harvest and its allocated quota (given by the coalition's quota share of $Q_2 + \Lambda$). As long as the coalition is able to appropriate its share of the increased quota, either by harvesting it or selling it, it will have incentives to engage in lobbying.[8] Thus, in this case the strategy of exerting lobbying effort to induce legislators to relax quotas is consistent with a Nash Equilibrium in which the largest coalition (e.g., firm or cooperative) contributes ψ while the rest of the fishery free rides (Freeman and Anderson 2017). It follows from our discussion that the behavior described in this section is more likely to arise in catch share fisheries where firms control multiple vessels or where cooperatives or sectors are present. Our application provides an example of such a setting. We will show that the largest businesses have strong incentives to individually lobby the regulator for higher quotas.

3. Application

3.1. **The Cod Fishery on Georges Bank.**

Cod's historical and cultural significance in New England is hard to overstate: the heart of immense mercantile wealth due to both its high quality and abundance led to an eponymous cape and the species depiction on the Massachusetts state capital building (Ropeik 2014). In federal waters, including our case study Georges Bank region,

[8]When the quota is not allocated to individual firms or coalitions of firms, the incentives to lobby the regulator will be lessened and depend on each coalition's ability to appropriate the benefits of lobbying by outcompeting others in the race for fish.

cod are managed in concert with fourteen other groundfish species as part of the New England Fishery Management Council's Northeast Multispecies Fishery due to jointness in production. The fishery is comprised of hundreds of vessels targeting species managed under the Northeast Multispecies Fishery Management Plan. The fishery is managed through what is termed a sector system, in which loose cooperatives of fishermen are allocated a proportion of a catch ceiling, known as an Annual Catch Limit (ACL), to harvest based on its membership's historical catch (Holzer and DePiper 2019, DePiper and Holzer 2024). This sector allocation is tradeable, and in practice functions akin to an individual transferable quota. In addition to these output controls, Northeast Multispecies are managed with input controls including both seasonal and year-round closed areas as well as mesh and other gear regulations that are intended to curb bycatch, targeting of spawning aggregations, and other issues unaddressed by the allocation of annual quotas. These input controls theoretically map to the vector $\boldsymbol{\theta}$ in eq. (1) by affecting when, where, and how fishing occurs, and thus fishermen's sampling regime and perception of stock status $\mu(\cdot|\boldsymbol{\theta})$.

Initially, managers envisioned sectors as a loose business unit where administrative duties would be centralized and efficiencies of scale and scope could be exploited, with the regulations stating that "sectors may pool harvesting resources and consolidate operations to fewer vessels, if they desire" (NEFMC 2010). Sectors may fish in an area as long as they hold unused quota for all fish stocks in that area. Coupled with jointness in production, this management system results in a phenomenon known as choke stocks: a single species at low abundance levels can close fisheries targeting other highly abundant species. Long the economic engine of the multispecies groundfish fishery, in recent years cod has become a choke stock (Horgan 2019). What is more, a deep divide exists between the scientific and fishermen's perceptions of the abundance of these cod stocks.

3.2. **Industry Beliefs.** Biases inherent in using data drawn from commercial fishing activities to estimate fish abundance have long been recognized in the scientific literature (Beverton and Holt 2012, Gulland 1964, J. E. 1964). These biases are driven in part by regulations, gear selectivity, and differential targeting behavior (Reimer, Abbott and Wilen 2017), which lead to nonrandom sampling regimes. Assessing and correcting the degree of bias is a topic of ongoing research (e.g. Saul, Brooks and Die 2020, Walter, Hoenig and Christman 2014). To deal with the bias of so-called fishery dependent data, biologists have long relied on stratified random sampling regimes using scientific surveys and standardized protocols to develop unbiased population-level inference.

The marked difference between data produced from scientific cruises versus fishing activity is also recognized by fishermen. However, their interpretation is that the stratified random sampling of the survey biases population estimates downward. “Everyone everywhere is saying there is no cod, but I have been up and down the coast and on and off shore looking, and I have seen cod everywhere. I could’ve rowed my boat with cod, there was so much.” (Hudson 2014, p. 42). The running arguments around cod population levels presents a vivid illustration of the issue. Vito Giacalone, a commercial fishery representative based in Gloucester, MA, has stated “You can’t just sample anywhere. You have to go to where the cod are supposed to be” (Abel 2017). More specifically, the Center for Sustainable Fisheries, whose Board of Directors is populated predominantly by commercial fishing interests, has similarly stated that “Cod are not evenly dispersed and such random sampling can easily miss large aggregations” (Cuddy 2023). Although there is obvious truth in the proposition that missing an aggregation of cod will impact population estimates, the number of standardized survey tows failing to catch cod has been increasing over time. In the 1970’s 42% of survey tows failed to catch cod, whereas in the 2010’s that proportion had increased to 65%, a statistically significant difference (χ^2= 164.99, df=1, p-value< 0.001) and strong signal that the population of cod has indeed declined. Moreover, the mean catch per positive tow has decreased significantly over time (20.2 kg/tow before 2000 versus 5.85 kg/tow after 2000; p-value < 0.001), suggesting that the biological survey is indeed capturing a decrease in the stock biomass rather than spatial aggregation alone.

It may seem odd for biased beliefs to persist in the face of overwhelming scientific evidence. However, these types of biases echo the “top of mind” biases that have been shown to be quite pervasive in human thinking. Similar reticence to changing beliefs can be seen in public discourses around climate change (Weber and Stern 2011, Egan and Mullin 2012, Akerlof et al. 2013, Myers et al. 2013, Herrnstadt and Muehlegger 2014) and the role of vaccinations in cases of autism (Davidson 2017), to name two high-profile examples.

Our illustration will assess the magnitude of economic incentives for industry to challenge official science flowing from biased perceptions and mistrust of management. To that end, we construct a counterfactual scenario in which fishermen's arguments against random sampling are taken at face value, as would occur if lobbying activity proved successful. We proceed by first recovering industry's beliefs on stock abundance, i.e., $\mu(\cdot|\boldsymbol{\theta})$ in eq. (2). This is accomplished by shifting the cumulative distribution of the scientific survey catch of cod to mimic the cumulative distribution of commercial cod catch at the same locations and during the same time of the year.

Figure 1 presents the mean commercial landings of cod on Georges Bank between 1996 and 2011, overlayed with biological survey tows represented as either positive or negative for (catching and not catching) cod. The figure highlights that a substantial number of survey tows on Georges Bank are negative for, or fail to catch, cod despite substantial commercial cod catch underlying the same area. Given the divergent aims of a commercial fishery and biological survey tows, this dichotomy is not unexpected and is likely attributable to (i) targeting behavior, seasonal and sub-seasonal changes in availability of the stock, gear selectivity and tow time, and (ii) restricted areas. Indeed, the figure highlights restrictions that can affect fishermen's perceptions in the form of two closed areas visible as discontinuous dark regions on both the western flank and eastern Canadian border of Georges Bank. These closed areas were originally implemented to avoid fishermen's targeting of spawning cod and haddock aggregations (New England Fishery Management Council 2016) and clearly illustrate the impact that restricting access can have on fishing effort. These divergences highlight the bias in fishermen's perceptions when compared to a random scientific assessment. We exploit these facts to derive our counterfactual fishermen's perspective on the stock.

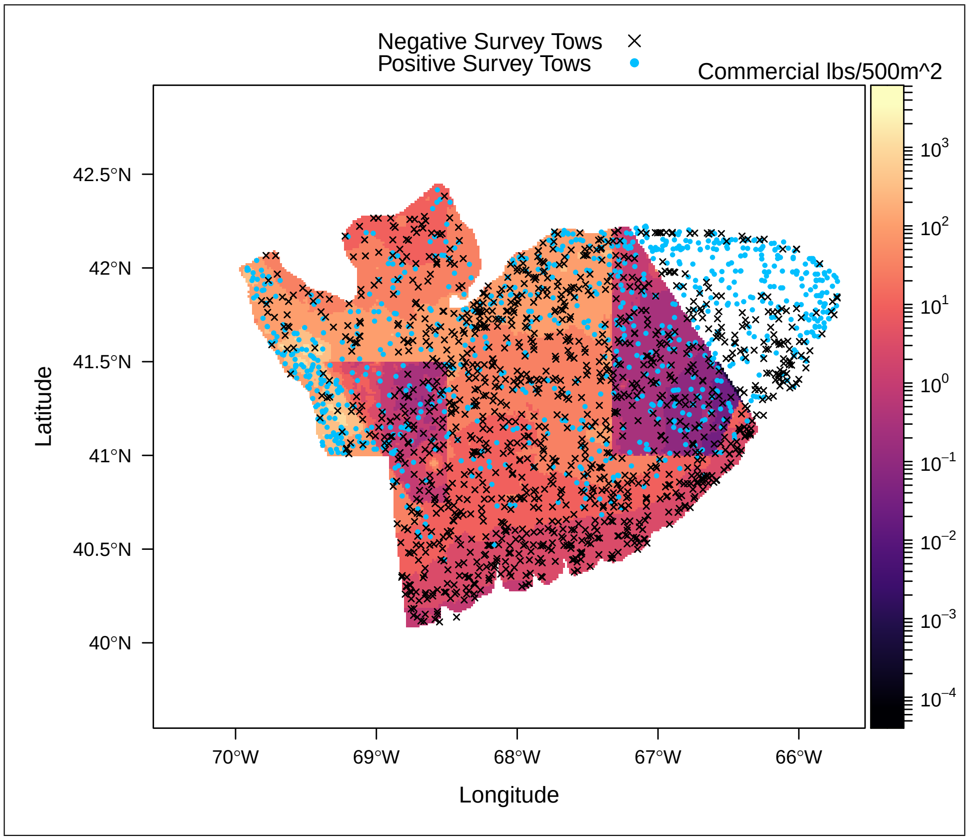

FIGURE 1. Positive and negative survey tows layered over average commercial catch in Georges Bank, 1996 - 2011. Survey tows over white background (northeast of the map) occur in Canadian waters, where US fishermen are excluded. Triangular regions (in purple) indicate closed areas to directed groundfish trips.

Our cod case study is motivated by fishermen indicating the survey is not catching fish, not that the size of the catch is low when the survey does encounter cod. Put another way, fishermen understand that a scientific survey's standardized speed, gear, and tow length impacts the total catch brought up in a haul and creates a divergence from the total catch their targeted and more flexible fishing activity achieves. However, fishermen expect that, conditional on this standardization, the relative catch between the biological survey and commercial tows should be similar. If fishermen are able to catch cod in a location, they expect that the survey should also be able to catch cod in that area. This rationale underlies the development of our empirical approach. The biological survey is conducted twice annually: once each in the fall and spring.

We therefore focus the development of our counterfactual within these two seasons. The top panel of Figure 3 presents two CDFs each for spring and fall: commercial catch of cod under negative survey tows (i.e., commercial catch at sites where the scientific survey caught no cod) and commercial catch under positive survey tows for cod. We calculate the distance between these CDFs in probability space. This vertical distance represents the difference in probability fishermen see in catch between the two areas, and thus forms a realistic representation of what they would anticipate to see as the difference between survey tows across the two areas. This probability distance is then used to shift up the positive survey tows distribution, creating a hypothetical distribution of negative survey tows that more closely represents commercial fishermen's perceptions of the stock across the two regions. Figure 2 illustrates this derivation of the CDF corresponding to the negative survey tows that would be consistent with fishermen's perceptions. The left panel (labeled (i)), displays a pair of known CDFs, F_1 and F_2, and the vertical distances between them for different quantiles, $q_i, q_j, q_k \ldots, q_n$ (e.g., first percentile, second percentile, etc.). These distances, shown as h_i, h_j, h_k, in conjunction with the known distribution μ_1, are used to find points a, b and c in the right-panel (panel (ii)). When this process is repeated for different quantiles, the resulting collection of points allows us to recover the CDF labeled as μ_2 in (ii) and shown as a dashed curve. The resulting distributions μ_1, μ_2 mimic, for the biological survey, the relative likelihood of catches −though not the magnitude of the catches themselves− that harvesters observe while fishing, as given by F_1, F_2.

The bottom panel of Figure 3 presents two CDFs each for spring and fall, with the blue curve representing −in each case− the derived CDF for our application to the Georges Bank cod fishery (i.e., equivalent to μ_2). Of note is that this probability shift implicitly encompasses not only differential fishing activities between commercial fishermen and biological surveys, but also the impacts of input controls on commercial fishing activities. Given that U.S. commercial fishermen have no real ability to catch cod in Canadian waters, we ignore the eastern tip of Georges Bank for this exercise. These new survey distribution functions are used to develop a counterfactual stock assessment, while holding survey data from Canada at observed levels as described below.

Annual indices of abundance provide information about the trend of the population. In the New England region, stock assessments frequently use a mean swept area index to inform the

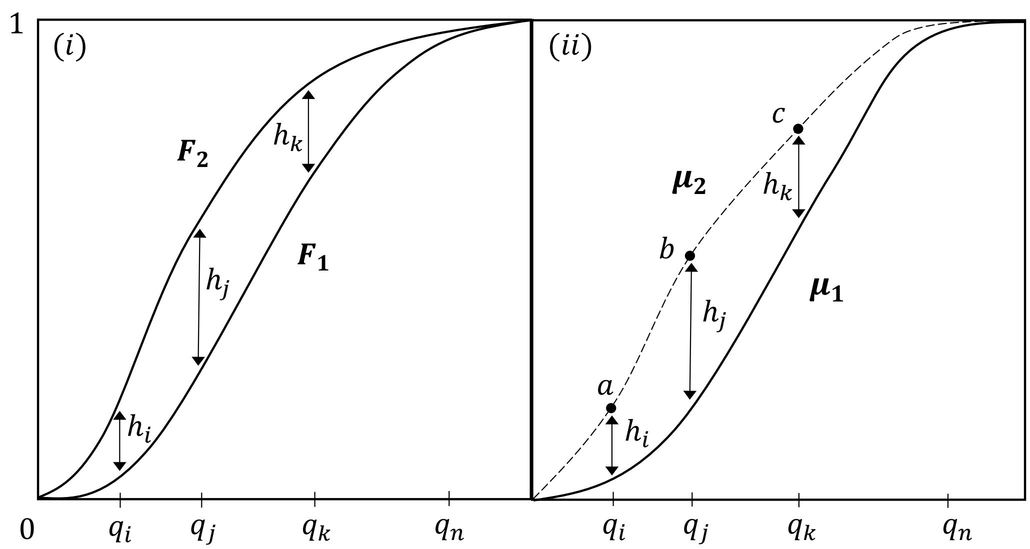

FIGURE 2. Graphical derivation of industry beliefs $\mu(\cdot|\boldsymbol{\theta})$. The left panel (labeled (i)), displays two known CDFs, F_1 and F_2, and the vertical distances between them for different quantiles, $q_i, q_j, q_k \ldots, q_n$ (e.g., first percentile, second percentile, etc.). These distances, h_i, h_j, h_k, together with the known distribution μ_1, are used to find points a, b and c in the right-panel (panel (ii)). When this process is repeated for different quantiles, the resulting collection of points allows us to recover the CDF labeled as μ_2 in (ii) and shown as a dashed curve.

assessment model about increases and decreases in stock size over the modeled years. From the stratified random sampling employed on the Northeast Fisheries Science Center Bottom Trawl Survey (NEFSC BTS), design based indices are calculated to obtain annual mean kg/tow or numbers per tow, and these means are then scaled up to the total area associated with a stock's management unit assuming the gear has catchability of 1.0 (in reality, catchability is < 1.0, hence the magnitude of the indices are considered "minimum swept area" biomass or abundance). To generate indices that reflect fishermen's beliefs $\mu(\cdot|\boldsymbol{\theta})$, the following algorithm was used. In each season, negative tows (i.e., a tow where no cod were caught) from the BTS are replaced by drawing a random number [0,1], and that value is matched to the empirical CDF derived from the hypothetical distribution of negative survey tows described above. After all negative tows are filled in this manner, the design based index is calculated by weighting the individual

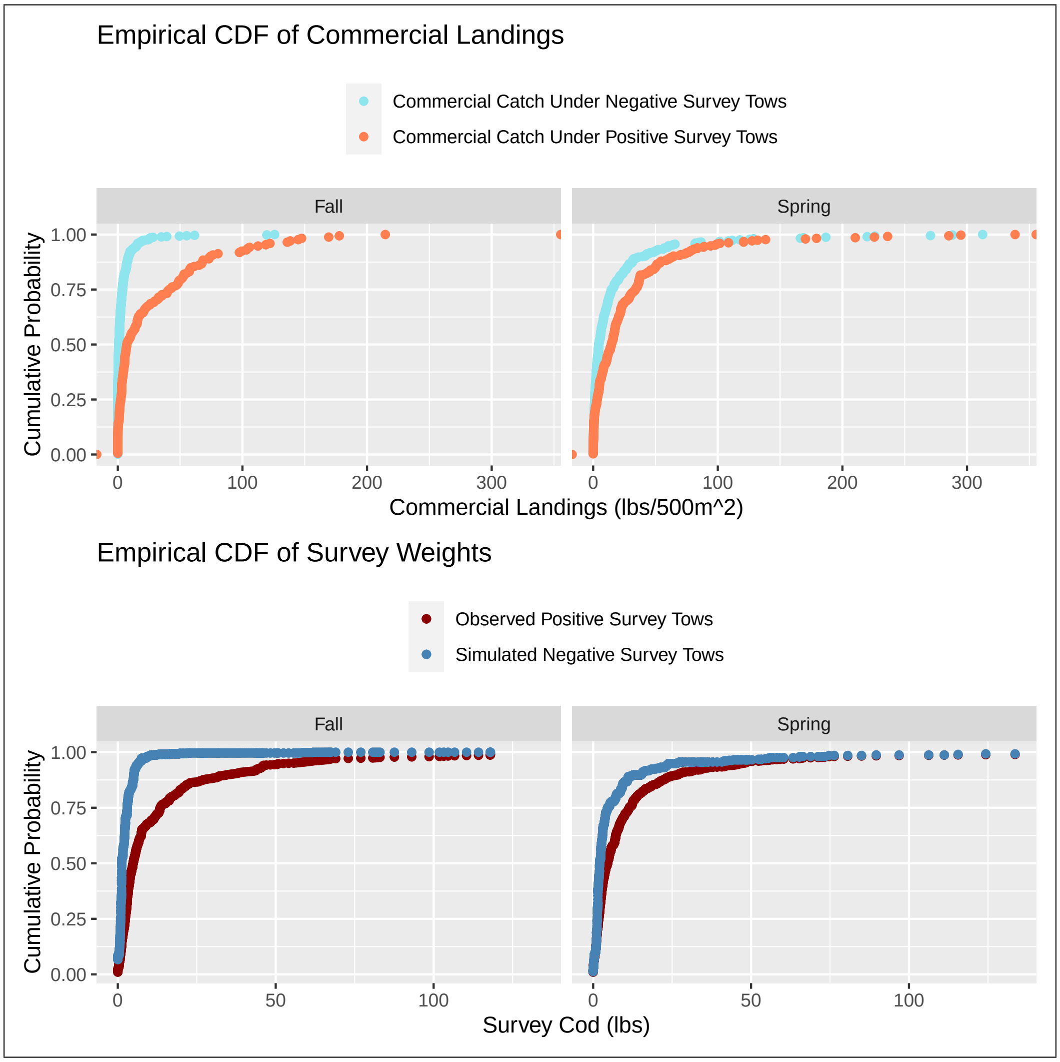

FIGURE 3. Cumulative distribution functions of commercial catch under positive and negative survey tows for cod (top panel), and the counterfactual survey index constructed by shifting the true survey cumulative probability up by the difference between commercial distributions (shown in blue in bottom panel), by season.

strata-specific means by the proportion of total area in each stratum. To better characterize the expected mean and variability from this hypothetical index, the process is repeated 100 times. The resulting indices when negative tows are simulated in this manner show an overall increased mean compared to the original index where negative tows were not removed (Figure A-1).

These indices are in units of biomass, but the stock assessment operates by tracking changes in abundance (numbers) and therefore the indices were converted to mean swept area abundance by dividing by the mean weight by year-season. The age composition (i.e. number of fish in each age class) of each season's annual index was assumed to be the same for the original and the simulated index, reflecting a difference in population magnitude only. Although the survey data used are from 1978 to present, vessel trip reports (VTR) with landings by latitude-longitude are only available from 1996. Our simulated survey therefore uses the original index values for years 1978-1995, and appends 1996-2011 to generate the new index.

3.3. **Stock Assessments.** A stock assessment is a model describing the population dynamics of a fish population, where increases in the number of fish in a given year are due to recruitment and decreases are due to both natural and fishing mortality. Although fishing mortality is estimated as an instantaneous rate, the rate of natural mortality is typically an assumed value because lack of direct observations of this process makes it challenging to estimate. The stock assessment provides estimates of abundance through the last year that data are available (typically one year earlier than the assessment is conducted), and then projections are made from the assessment results to explore sustainable levels of harvesting in future years. The assessments are reviewed by an external panel of experts, sensitivity of results are examined, and robustness of advice is explored.[9] If the assessment passes this peer review, then the results are provided to managers who then oversee implementation of the assessment estimates of future ACLs. While no model is ever assumed to be 100% accurate, an assessment that passes rigorous peer review is treated as 'Best Scientific Information Available (BSIA)' and is used as the basis for management.[10] Assessments are updated regularly, new information is evaluated for potential inclusion, and subsequent peer reviews are conducted. This provides frequent feedback on the assessment model, the data that inform the model, the appropriateness of assumptions, and the robustness of advice.

The stock assessment model framework that had been used until recently to assess Georges Bank cod is the Age Structured Assessment Protocol (ASAP, Legault 1999), a forward projecting

[9]See `https://d23h0vhsm26o6d.cloudfront.net/NRCC_Assessment_Process_Version-18Feb2022_508.pdf`

[10]`https://www.federalregister.gov/documents/2013/07/19/2013-17422/magnuson-stevens-act-provisions-national-standard-2-scientific-information`

statistical catch-at-age model. The model is fitted to fishery catch (total landings and discards, and their estimated age composition), fishery independent data (mean annual abundance and age composition for spring and fall NEFSC BTS, and a spring BTS by the Department of Fisheries and Oceans, Canada). Total catch and mean annual indices are modeled assuming lognormal error, and age composition data are fitted assuming a multinomial distribution. Over the period for which data are available, the variance in spawning stock biomass (SSB) is low while the variability in estimated recruitment is large, contributing to the inability to fit a stock recruitment function other than a mean with lognormal annual deviations. The assessment model results are the estimates that maximize the joint log-likelihood from fitting each data component (catch, indices, and their associated age composition). For details see section A-1 in the appendix. The estimated parameters for this illustration include: mean recruitment and annual deviations from that mean, a mean fishing mortality rate and annual deviations, a catchability for each survey index (there are 3 surveys), a selectivity for each index (this is a vector with probability at age that the vessel will capture each age class that it encounters), selectivity for the fishery (an age-specific vector of capture probability, two separate time blocks assumed). Lastly, the initial numbers at age in the first model year are estimated as deviations from an exponential decline.

Two stock assessments were conducted using this modeling framework for the Georges Bank cod stock. The first was simply rerunning the base model from the 2012 benchmark assessment, which we refer to as the "Manager's Perspective" model below (Northeast Regional Stock Assessment Workshop 2013). The second was to replace the two NEFSC BTS indices with the simulated indices that reflect fishermen's beliefs, $\mu(\cdot|\boldsymbol{\theta})$, keeping all other assessment data and model settings the same (referred to as "Fishermen's Perspective" below). Although this cod assessment took place 10 years ago, we use the 2012 benchmark because it was the last time that an age-based assessment was accepted for management use. When the model was updated in 2015, it was rejected by peer reviewers due to an extreme retrospective pattern and the stock is now assessed using a simpler method that sets quota by scaling recent quota by a three-year average trend of fishery independent surveys. This simple method has no projection capability and is therefore not suitable for exploring our counterfactual example.

Both assessment models converged, which was determined by the maximum gradient being less than 10^{-4} and the hessian being positive-definite. Following the minimization routine, we perform Markov Chain Monte Carlo (MCMC) simulations retaining 1,000 iterations given a thinning rate of 200. The saved MCMC values characterize the uncertainty in model estimates, and also provide 1,000 unique estimates of numbers-at-age at the end of the final model year from which projections of future outcomes can be simulated.

The estimated trajectories of SSB are similar for the two models from 1978-2003, but they begin to diverge in 2004 and by 2007 there is almost no overlap in their estimated distribution of SSB. As expected, the SSB trajectory from the *Fishermen's Perspective* model using the simulated indices is markedly higher than the *Manager's Perspective* assessment SSB trajectory, which reflects fishermen's belief that abundance is higher than estimated by the scientist's original stock assessment. While the estimated SSB for the final model year (2011) is nearly double for the *Fishermen's Perspective* assessment (47,310 metric tons vs 22,058 mt), both assessments have a retrospective pattern that requires adjusting the terminal year estimates prior to making stock projections (Mohn 1999; Legault 2009). A retrospective pattern is a diagnostic that compares assessment estimates from the full time series of a given model, with estimates from the same model with $y = 1, 2, \ldots, 7$ years removed (these models with sequentially removed years of data are often referred to as 'peels'). When looking across the estimates available in each peel, one expects some variability. However, when the variability is unidirectional this is interpreted as 'retrospective bias', and indicative of a mismatch between data and model assumptions. Often, SSB estimates in the peels are seen to be adjusted downwards when an additional year of data is added. When averaging these deviations in sequential estimates relative to the full time series, a value near zero indicates no retrospective pattern. For this illustration, the *Manager's Perspective* model had a value of 0.681 while the *Fishermen's Perspective* model had a value of 1.520, indicating a large and very large retrospective pattern, respectively. In the presence of retrospective bias, past research has demonstrated that bias in future catch advice is reduced if projections account for this terminal year pattern (Legault 2009; Brooks and Legault 2016). A scalar adjustment to the assessment model estimates of starting numbers at age in the first projection year is calculated from the measure of retrospective pattern: scalar=1/(retrospective value). For the two assessments conducted for this application, this leads to scaling the *Manager's Perspective* model by 0.595 and the *Fishermen's Perspective* model by 0.397. This retrospective adjustment brings the final year estimates of the two models closer, but the estimate from the *Fishermen's Perspective* model is still larger.

Future quotas and population trajectories are calculated by projecting the stock dynamics into the future, where either catch or a fishing mortality rate is specified each year. Below, we detail the standard approach used in the Northeast U.S. to set quotas and assess future population dynamics in federal fisheries management and employed in this research. The standard approach for estimating future catch is to use 75% of the fishing mortality rate ($\mathbb{F}$) which generates Maximum Sustainable Yield (MSY), or its proxy. Because no functional form (e.g., Beverton-Holt) is used for the stock recruit relationship, there is no defined MSY solution and instead a proxy based on expected lifetime reproduction is calculated. Specifically, the fishing mortality rate that reduces expected lifetime reproduction to 40% of unexploited levels ($\mathbb{F}$40%) is the FMSY proxy. The assessment was conducted in 2012, and therefore fishing in that year was already taking place, making it more practical to specify an expected amount of catch for the remaining months of the year rather than specifying a fishing mortality rate. The expected catch for the year 2012 was 2,910 mt; all subsequent years of the projection specified a fishing mortality rate of 75% of $\mathbb{F}$40% (0.135). In the projections, biological characteristics such as weight at age and maturity at age, as well as the fishery selectivity, are unknown quantities because there are no observations from which to estimate them. As is customary, projections employ a simple average of the most recent 3 years for each quantity. Future recruitment in year y is drawn from a 2-stage empirical CDF defined by whether SSB in $(y-1)$ was above or below a threshold of 50,000 mt (there is a greater probability of larger recruitment when SSB is above this threshold). From each of the saved 1,000 MCMC initial conditions, 100 population trajectories are simulated, producing a total of 100,000 simulated projections. Projections were made from the initial conditions for the *Manager's Perspective* and *Fishermen's Perspective* model. Once these projections were made, the results from the *Fishermen's Perspective* model were used to specify a third projection scenario, which we refer to as the "Manager's Perspective with Depletion" projection. Catch in 2012 was still set at 2,910 mt, but catches for years 2013-2030 were set to the median catch from the *Fishermen's Perspective* projection. This

Manager's Perspective with Depletion scenario illustrates the outcome of removing the higher catches (premised on fishermen's belief that population abundance is higher, as indicated by the simulated indices) from the expected *Manager's Perspective* population trajectory. This scenario highlights the results of fishermen's successful lobbying for higher quotas with biased beliefs in the true status of the stock.

Projected catch and spawning stock biomass from both the *Manager's Perspective* and *Fishermen's Perspective* assessments show increasing trajectories. Catch in the first projection year (2012) is identical, due to the imposed assumption of what catch is likely to be taken in that year, but in subsequent years the median catch for the *Fishermen's Perspective* scenario exceeds the upper 95% probability interval of the *Manager's Perspective* assessment scenario for the next 9 years (Figure 4). Similarly, median spawning stock biomass from the *Fishermen's Perspective* scenario exceeds the upper 95% probability interval of the *Manager's Perspective* scenario for the first decade (Figure 5). When the median catches from the *Fishermen's Perspective* projections are removed from the population as estimated from the *Manager's Perspective* assessment model (*Manager's Perspective with Depletion* scenario), we see that SSB increases more slowly than the other two projections, and by 2021 the population begins declining and has effectively crashed by 2025. The crash is driven by removing catches that are not sustainable, and we see that the *Fishermen's Perspective* catches can only be consistently removed through 2021, and from 2022-2030 there are iterations where the full amount of catch specified could not be removed from the population.

3.4. **Industry Incentives.** Recall that the stock assessments project three different states of the world: the *Manager's Perspective* scenario drawn from the scientific survey, our counterfactual *Fishermen's Perspective* on the stock, and a third scenario of *Manager's Perspective with Depletion*, in which the original stock dynamics drawn from the survey are subject to harvest at the higher rate dictated by fishermen's perceptions. This latter scenario represents what would happen to the stock if lobbying was successful but fishermen's perceptions were incorrect. Table 1 shows the results of the Barrett and Donald (2003) tests for first-order stochastic dominance, which confirm that the SSB distribution for the *Manager's Perspective* scenario is stochastically dominated every year in the period 2013-2030 by the *Fishermen's Perspective* SSB distribution.

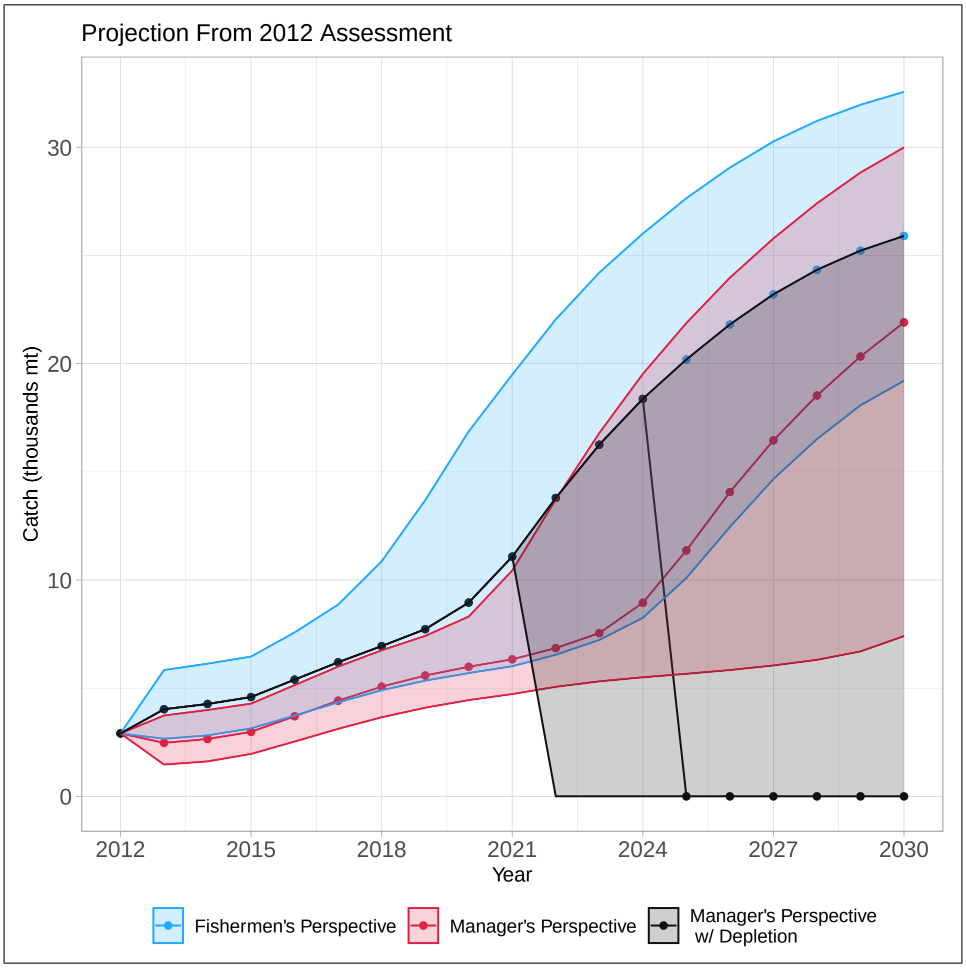

FIGURE 4. Projected catch for Georges Bank cod for three scenarios: the M*anager's Perspective* assessment (red), *Fishermen's Perspective* model (blue), and the *Manager's Perspective with Depletion* model (black) where median catch from the *Fishermen's Perspective* model is removed from the population as estimated by the *Manager's Perspective* assessment. Catch in 2012 was specified to be 2,910 mt for all models, and in subsequent years the distribution of catch from fishing at 75% of $\mathbb{F}40\%$ (0.135) are calculated. Shaded regions indicate 5th and 95th percentiles, while solid line with solid circles indicates the median.

As outlined in section 2, the stochastic dominance results indicate that fishermen's expectation of stock status is significantly higher than the manager's.

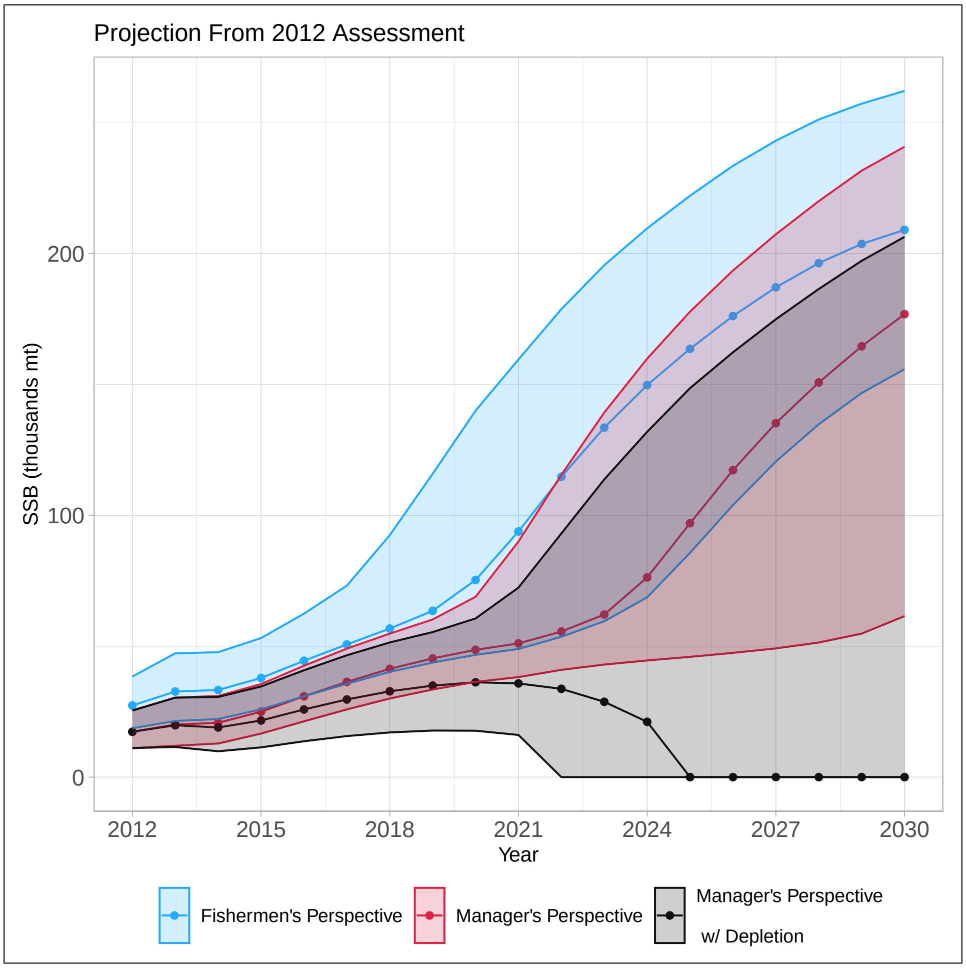

FIGURE 5. Projected spawning stock biomass (SSB) for Georges Bank cod for three scenarios: the *Manager's Perspective* assessment (red), *Fishermen's Perspective* model (blue), and the *Manager's Perspective with Depletion* model (black) where median catch from the *Fishermen's Perspective* model is removed from the population as estimated by the *Manager's Perspective* assessment. The difference in SSB in 2012 reflects the different initial population numbers, as estimated from the *Fishermen's Perspective* and *Manager's Perspective* assessments (i.e., blue is *Fishermen's Perspective* initial conditions, while both red and black are the initial conditions from the *Manager's Perspective* assessment). Shaded regions indicate 5th and 95th percentiles, while solid line with solid circles indicates the median.

We simulate the distribution of the Net Present Value (NPV) across scenarios and the projected time horizon as follows. Gross revenue on multispecies groundfish trips landing Georges Bank cod are derived based on the value of all species landed during the trip, as recorded in the Federal commercial dealer database. This represents the legal record of all cod landings from the U.S. waters of Georges Bank. Variable costs for that same trip are then estimated based on the approach outlined in Werner et al. (2020). Table A-1 in the appendix presents parameter estimates of the cost model for Bottom Trawl, the most common gear used in the groundfish fishery. Crew in this fishery are traditionally remunerated through the lay system, in which they receive a portion of either gross or net revenue for their services. Although a lack of lay standardization exists, we assume crew receive 50% of net revenue as their share. This is both a common split and suffices to highlight the magnitude of incentives at play within fisheries management (Georgianna et al. 2011, Murphy et al. 2015). We estimate net revenue for all Georges Bank cod trips occurring between 2013 and 2019. Table 2 presents summary statistics for the pooled data, deflated to 2023 constant dollars.

TABLE 1. 2013 - 2030 Test of SSB First Order Stochastic Dominance

Statistic	FSD Observed	p-value
2013	Yes	1.0000
2014	Yes	1.0000
2015	Yes	1.0000
2016	Yes	1.0000
2017	Yes	0.9995
2018	Yes	0.9995
2019	Yes	1.0000
2020	Yes	1.0000
2021	Yes	1.0000
2022	Yes	0.9990
2023	Yes	0.9990
2024	Yes	1.0000
2025	Yes	1.0000
2026	Yes	0.9990
2027	Yes	1.0000
2028	Yes	0.9980
2029	Yes	1.0000
2030	Yes	1.0000

Note: If the null $H_0 : G \succcurlyeq_{FSD} F$ cannot be rejected at conventional significance levels, the SSB distribution for the *Fishermen's Perspective* model (G) first-order stochastically dominates the SSB distribution corresponding to the *Manager's Perspective* model (F).

The simulations employ block-sampling, in which we first randomly select a year then draw with replacement from that year's trips until the cumulative trip catch for cod achieves the annual catch limit as estimated from the stock assessments under each scenario. The block sampling controls for intra-year correlation in input and output prices, and the use of 2013 - 2019 trip information ensures that results are not a quirk of unrepresentative economic or ecosystem conditions within a shorter time horizon. We exclude information beyond 2019 due to the impacts of COVID-19 on seafood supply and demand. This approach is repeated for each of the projected years. We develop 4,000 replicate draws of ACLs and trips for each scenario. All simulations assume that cod remains the choke species in this fishery. Figure 6 presents the mean and 95% confidence intervals of the undiscounted owner's share of simulation results. There is a clear separation of outcomes between the *Manager's Perspective* and *Fishermen's Perspective* scenarios, with fishermen's perceptions dominating the original survey results. The mean net revenue from the *Manager's Perspective with Depletion* scenario tracks the *Fishermen's Perspective* outcome until a decade into the simulations, at which point the stock can no longer support the higher catch rates. Table 3 presents the NPV calculated across simulation scenarios. In the management context, stock assessments for cod are currently updated every two years using model projections to set regulations, and the stock assessment is not used to set regulations in the year they are run. This translates into a three year window in which the parameters of the stock are fixed and identifies the relevant time horizon of interest for assessing gains that could be derived from lobbying for higher quotas. Thus, in Table 3 we delineate NPV estimates for this three-year horizon. These estimates are undertaken using three different discount rates: 2% and 7%, as suggested by U.S. federal guidelines on implementing Cost-Benefit analyses, along with 11.6% which equals the 10 year average yield from the ICE BofA CCC & Lower US High Yield Index,[11] e.g., risky assets.

3.4.1. *Manager's vs Fishermen's Perspective Scenarios.* Even under a three year time horizon, the numbers are substantial with a mean difference between the *Manager's Perspective* NPV and the *Fishermen's Perspective* counterfactual ranging from a high of \$85 million under a 2% discount rate to a low of \$70 million under the 11.6% discount rate. This translates into a 72-73% increase in value that is apparently (i.e., in the eyes of the industry), but not actually, achievable through lobbying activities across all three discount rates. As previously stated in Section 2, the decision to lobby for these increased ACLs does not depend on a Nash Equilibrium across all owners, merely that a subset of owners stand to gain enough to justify the investment. To highlight this issue empirically, table A-2 in the appendix presents the NPV estimates for the three largest fishing entities active in the Georges Bank cod fishery. For these three entities

[11]Sept. 25, 2013 - Sept. 25, 2023; downloaded from `https://fred.stlouisfed.org/series/BAMLH0A3HYCEY` on September 25, 2023.

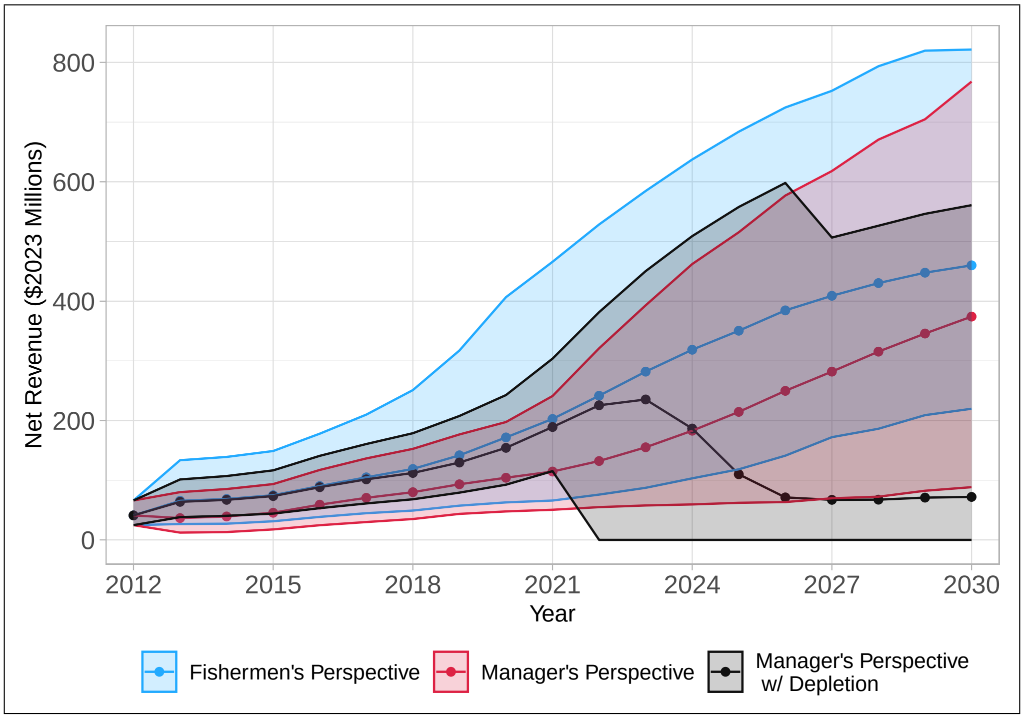

FIGURE 6. Time series of net revenue for all years of the simulations, by scenario.

alone, a successful lobbying campaign could be expected to engender between \$17 million and \$20 million over a three year period, dwarfing the amount that would be needed to hire a full-time lobbyist over that same time period. These figures indicate that, were the industry to have 100% confidence in their own observations and completely disregard the official science, i.e., $\rho = 1$ and $G(\cdot|\rho, \boldsymbol{\theta}) = \mu(\cdot|\boldsymbol{\theta})$, their beliefs would lead them to expect large returns to lobbying for more lax regulations.

Table 2. Net Revenue Summary Statistics (All Georges Bank cod trips 2013-2019)

Variable	Mean	Median	Std Dev	Min	Max	N
Gross Revenue	$26,010	$11,947	$28,435	$0	$181,621	13,527
Trip Costs	$6,960	$3,575	$7,850	$3	$39,912	13,527
Fifty Percent Owner Share Net Revenue	$8,873	$3,520	$10,641	-$9,105	$78,488	13,527

Table 3. Three-Year Net Present Value under different discount rates (Millions of dollars)

Simulation	Discount Rate	Mean	Median	Std. Dev.	Min	Max
Fishermen's Perspective	0.020	\$201	\$193	\$65	\$54	\$524
Manager's Perspective	0.020	\$116	\$111	\$44	\$12	\$374
Manager's Perspective w/ Depletion	0.020	\$196	\$196	\$37	\$49	\$311
Fishermen's Perspective	0.070	\$182	\$175	\$59	\$49	\$476
Manager's Perspective	0.070	\$106	\$100	\$40	\$11	\$340
Manager's Perspective w/ Depletion	0.070	\$178	\$178	\$33	\$47	\$282
Fishermen's Perspective	0.116	\$167	\$161	\$54	\$45	\$438
Manager's Perspective	0.116	\$97	\$92	\$36	\$10	\$313
Manager's Perspective w/ Depletion	0.116	\$164	\$163	\$31	\$45	\$259

3.4.2. *Manager's Perspective vs Manager's Perspective with Depletion Scenarios.* As stated earlier, the *Manager's Perspective with Depletion* scenario illustrates the outcome of removing the higher catches from the expected *Manager's Perspective* population trajectory. It highlights the consequences of fishermen's successful lobbying for higher quotas (based on biased beliefs $G(\cdot|\rho = 1, \boldsymbol{\theta}) = \mu(\cdot|\boldsymbol{\theta})$) on the true status of the stock. How does this scenario compare with the *Manager's Perspective* status quo scenario in which industry follows the prescriptions of the official science and catch limits are set more conservatively? In Table 3 the *Manager's Perspective with Depletion* scenario provides a better outlook in the in the eyes of the industry than the *Manager's Perspective* scenario, with gains that range from \$80 million under a 2% discount rate to \$67 million under the 11.6% discount rate. The corresponding figures for the three largest businesses range from \$19 million under a 2% discount rate to \$16 million under the 11.6% discount rate. Thus, in the short-term the incentives to lobby the regulator remain strong even in the presence of depletion. This is to be expected as a three-year time horizon is not long enough for the excess harvest resulting from lobbying to have a significant impact on stock status.

In sum, as the comparisons in 3.4.1 and 3.4.2 illustrate, whether the industry is correct in its assessment of the stock (i.e., in which case *Manager's* vs *Fishermen's Perspective* is the relevant comparison) or not (i.e., *Manager's Perspective* vs *Manager's Perspective with Depletion* is the relevant comparison), it pays for harvesters to engage in lobbying activities in the short-term. As we show next, those incentives remain strong when considering a longer time horizon.

3.4.3. *Longer Term Incentives.* The appeal of lobbying for higher quotas comes down to two subjective issues: 1) fishermen's discount rate (impatience); and 2) the degree of confidence fishermen have that they are correct in their beliefs. To the latter point, fishermen are likely to entertain some probability that the science is correct, that is, that the claims put forward by management regarding stock status are true. Although we cannot readily identify either a fisherman's discount rate or confidence in their own beliefs, we can vary these parameters to assess their impact on a fisherman's incentive to lobby. Concretely, we study how the incentives to lobbying vary as we change the industry's discount rate and the probability $(1-\rho)$ harvesters attach of being wrong in eq. (2), that is, that the *Manager's Perspective with Depletion* scenario comes to be.

Moreover, since industry would anticipate learning about the true status of the stock as the seasons go by, we allow harvesters to adjust their beliefs based on the signals the receive while on the water. We proceed as follows. Fishermen observe the net revenue generated in any year, and assess where that value falls within the two relevant distributions of net revenue: the *Fishermen's Perspective* based on $\mu(\cdot|\boldsymbol{\theta})$ and the *Manager's Perspective with Depletion* based on F. These two distributions encapsulate the two possible outcomes when fishermen are successful in lobbying activities, the former if they are right and the latter if they are wrong. It is reasonable to assume that the weight placed on either scenario being correct should drop to zero if the observed net revenue falls outside of that scenario's distribution. Given the motivation for this research, the learning is assumed to begin with the distribution of revenue from the *Fishermen's Perspective* scenario. If the observed net revenue falls in the lower 50% of the *Fishermen's Perspective* net revenue distribution, we assume ρ is decreased based on how close the observation is to exiting that distribution. Conversely, if the observed net revenue falls within the upper 50% of the *Fishermen's Perspective* distribution, we assume ρ is increased based on how close the observation is to exiting the upper tail of net revenue generated by the *Manager's Perspective with Depletion* scenario.

Discretizing the left-hand side of eq. (5) when beliefs each season t are given by $G(\cdot|\rho_t, \boldsymbol{\theta}) = \rho_t \mu(\cdot|\boldsymbol{\theta}) + (1 - \rho_t)F$, fishermen will prefer lobbying over the status quo scenario if the NPV calculated using the linear combination of yearly flows from the *Fishermen's Perspective* and *Manager's Perspective with Depletion* scenarios, each weighted by the subjective probability at t of that scenario being correct, is at least as large as the NPV derived from the *Manager's Perspective* scenario. To provide an assessment of the incentive to lobby within the fishery under different confidence levels and discount rates, we apply the corresponding analysis to the aggregate NPV derived from each of the scenarios. The top panel of Figure 7 presents the difference between the NPV using the weighted flows from the *Fishermen's Perspective* and *Manager's Perspective with Depletion* scenarios and the NPV from the *Manager's Perspective* scenario for discount rates ranging between 0.02 and 0.116. The weights are derived by varying the initial subjective probability of the *Fishermen's Perspective* scenario being correct (ρ) from 0.01 to 1.0, labeled as Confidence in Figure 7, and letting that initial weight be updated −increased or decreased− as the industry learns the true status of the stock. Under the learning algorithm described earlier, by 2027 harvesters will know with certainty that the *Manager's Perspective with Depletion* is the true scenario and stop lobbying. However, by then the stock will already be depleted (i.e., the spawning stock biomass drops to zero in 83.7% of the draws in 2027), forcing the regulator to put the fishery into a rebuilding plan.

The top panel of the Figure 7 highlights that fishermen's confidence in their own beliefs need not be absolute in order to make lobbying for higher quotas an appealing strategy. In fact, even under the lowest discount rates and confidence levels ρ, fishermen will expect lobbying to lead to net gains. The fact that the difference in NPV is always positive and sizeable indicate that substantial incentives to lobby can exist *even if* fishermen have relatively low confidence in their beliefs on the status of the cod stock, and are able to update these beliefs based on signals derived from their own fishing activity. Critically, these are gains the industry expects based on biased beliefs and that do not materialize. As shown in the bottom panel of Figure 7, the actual consequences of lobbying and higher quotas on the stock are depletion and welfare losses. The foregone discounted revenues, i.e., the additional net revenues industry would have earned in 2013-2030 if trusting the official science and refraining form lobbying, range from \$520 million to \$7.7 million depending on the discount rate. This stark difference between the expected and realized consequences of lobbying in Figure 7, can be ascribed to both the industry overreliance on their own observations and the slow pace of their learning (i.e., convergence of $\rho \to 0$) due to uncertainty in the system (see Figure 5 for uncertainty in the stock assessment). This uncertainty implies that harvesters receive noisy signals that may lead them to increase ρ in some seasons (i.e., beliefs change non-monotonically). Figure A-2 presents the same figure for the top three businesses engaged in fishing for Georges Bank cod. It shows a similar pattern. Again regardless of discount rate, not much confidence is needed in one's own beliefs in order for lobbying to lead to substantial expected gains in the eyes of the industry. Thus, fishermen will expect high returns in seeking higher harvest quotas. Ultimately, however, this strategy if successful (e.g., under regulatory capture) would undermine fishermen' own interests, as the cod depletion translates into long-term losses.

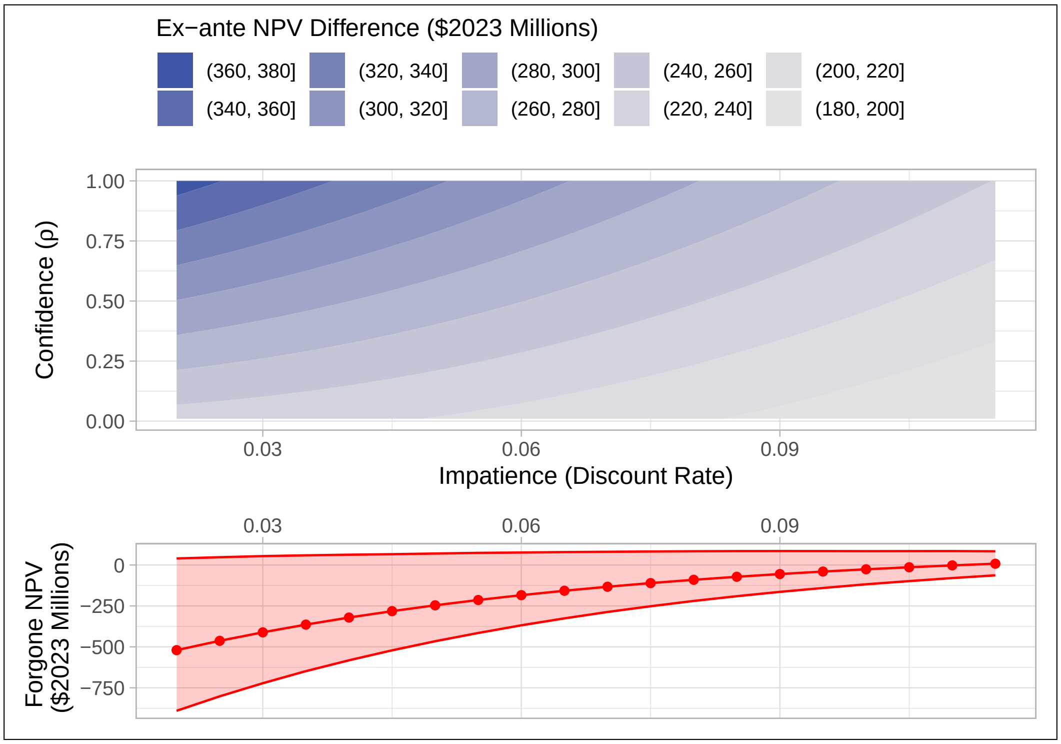

Figure 7. Top panel: difference between NPV calculated using weighted flows from the *Fishermen's Perspective* and *Manager's Perspective with Depletion* scenarios and NPV from the *Manager's Perspective* scenario for varying discount rates and initial confidence in a Fishermen's own beliefs over the science (ρ). That initial ρ is updated over time as harvesters receive signals on profitability (i.e., based on differences in net revenue under the *Fishermen's Perspective* and *Manager's Perspective with Depletion* scenarios). Bottom panel: mean and 95% confidence interval for the foregone (discounted) net revenue the industry would have earned over the period 2013-2030 if it had accepted the *Manager's Perspective* and not engaged in lobbying.

4. Conclusion

Mistrust and conflict between industry and regulators is a constant in commercial fisheries management. A common manifestation of such conflict is the fishing industry's hiring of consultants and professional lobbyists to challenge the science that informs management. Divergence of objectives and incentives are typically invoked to explain this pervasive phenomenon: short-term profit maximization in the case of the industry versus long-run resource sustainability in the case of the manager (Parés, Dresdner and Salgado 2015). In this paper we explore an alternative rationale for the ingrained friction between these stakeholder groups. We develop a theory to argue that harvesters' overreliance on personal experience, a universal human tendency (Barron and Erev 2005, Weber 2010), may contribute to the protracted conflict between industry and regulators. Relying primarily on experiential samples, i.e., samples of the population collected while fishing, harvesters form biased beliefs because they fail to recognize the lack of representativeness of those samples. Moreover, in an industry where the productivity of the fish population is ever changing and hard to assess even for stock assessment experts, updating harvesters' beliefs may be difficult. Thus, the conflict stemming from the different views on resource productivity can be long-lasting (Adams, Brockington and Vira 2003). Frictions between the industry and the regulator are not a rarity in other sectors of the economy. However, the possibility of regulatory capture makes commercial fishing stand out (Peña Torres 1997, Turner and Weninger 2005, Costello and Grainger 2018). If industry's challenge of the official science prevails, biased beliefs on stock productivity may ultimately lead to over-harvesting and welfare loss.

In the application of the theory to the Georges Bank cod fishery, we rely on fishermen's own testimonies to elicit their beliefs on the results of a fishery-independent survey in a manner consistent with their personal experience. We then use these *adjusted* survey results to update the latest stock assessment and set annual catch limits that would be consistent with industry beliefs on stock abundance. Finally, we use landings data and information on costs and expenditures at the trip level to estimate the distribution of extra profits the industry would expect in this scenario over the three years until the next stock assessment. For the industry, we find sizable short-term gains from engaging consultants who question the science that managers rely on to set policy: a mean of over \$70 million in extra profits (roughly a 72% increase) over the three-year period. This strategy would eventually lead to the collapse of cod, and to welfare losses under a realistic range of social discount rates. We show that even low confidence in their own beliefs could lead the fishing industry to lobby against their own long-term interests. Notably, our model does not rely on the existence of bad actors, as we show that challenging of the official science can arise as a natural outcome of differences inherent in fishermen's on-the-water experience and scientific sampling regimes. More problematically, management can inadvertently exacerbate the bias in fishermen's perceptions by instituting input controls specifically aimed at changing when, where, and how fishing occurs. We conclude that the incentives associated with the additional profits that would be obtained if science were consistent with harvesters' personal fishing experience help explain the common industry practice of hiring lobbyists to voice concerns at regional councils' Scientific and Statistical Committee meetings, as well as at the stock assessment meetings.

Our findings highlight the importance of effectively communicating and translating the technical aspects of science to the relevant audiences, particularly those directly impacted by its use in policy. As discussed in this paper, both the scientific sampling methods and the stock assessment process central to fisheries management are technical in nature, and not accessible to those outside the field. Hence, nonspecialists lack understanding and trust of the science that supports stock assessments (Calderwood et al. 2023). This lesson is not specific to commercial fishing, as other industries share the key features of the setting we study: i) a changing stochastic environment that must be regulated; ii) reliance on science to set regulations; iii) complexity of the science involved; and, iv) discrepancy between regulated parties' daily experience and the claims of official science. Climate change adaptation policies and the fight against infectious diseases via vaccination programs are just two additional examples. There is a growing consensus that for effectively communicating complex issues such as climate change, information must be presented with a focus on the real world rather than with abstractions, and aiming for a narrative structure that shows the human face behind the science (Simms 2015, Climate Outreach 2018). However, this is not enough, as who provides the information also matters. Recent experiences recruiting and training non-specialists to communicate the science to peers have proven effective. As an example, take the case of the *Shots at the Shop* program, which engages Black-owned barbershops and hair salons nationwide to act as health advocates and assist their clients in making informed COVID-related decisions, and hosting COVID-19 vaccination clinics in their shops (Linnan, Thomas and Passmore 2022).[12] The Marine Resource Education Program (MRE) is a similar initiative in the context of commercial fisheries.Funded by NOAA and the National Marine Sanctuary Foundation, and administered by the Gulf of Maine Research Institute, MRE offers workshops for fishermen to: "learn the nuts and bolts of

[12]For further details see: https://sph.umd.edu/shotsattheshop

marine fisheries science and management, demystify acronyms and vocabulary, gain tools and insights into effective engagement in their regional Fishery Management Council, and connect with key regional fishery science and management experts."[13]

Moreover, long-term cooperative research among fisheries scientists, managers and industry, such as the Massachusetts Division of Marine Fisheries Industry-Based Survey[14], can help identify biases in the parties's perspectives and lead to greater mutual understanding, trust, and likelihood of long-lasting partnerships (Hartley and Robertson 2006, Daw, Robinson and Graham 2011). However, to be effective, cooperative research must directly involve stakeholders, particularly the fishing industry, at each step of the project, from design through execution (Hare 2020, Dean et al. 2023).

This paper shows that the policy instruments that managers adopt not only enforce conservation measures, but also determine what dimensions of the resource users actually observe. In turn, the way users are allowed to *sample* the resource determines their beliefs on resource productivity and their incentives to challenge those regulations. Thus, when selecting policy instruments, managers should be mindful of both dimensions: i) the conservation, and the ii) informational (signalling) aspects of policy. As shown in this work, proceeding otherwise may undermine the very purpose of those policies. For example, managers may consider alternate conservation policies like rotational area closures that allow the industry to explore different aspects of the stock while achieving similar fishing mortality. Under this strategy, the regulator would need to adjust the precautionary quota buffers associated with management uncertainty to limit the probability of overfishing under the alternating policy options.

[13]https://mrep.gmri.org/apply

[14]For details see: https://www.mass.gov/info-details/industry-based-survey-for-gulf-of-maine-cod

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5. Appendix

A-1. Population Dynamics and Forecasting

The age-structured population dynamics equations in the stock assessment software package ASAP (Legault 1999), used in this research, are as follows. The time step of the model is one year, and recruitment occurs at age 1. Recruitment can be modeled as a function of spawning biomass or as a constant with annual deviations. For this application to Georges Bank cod, a functional form was inestimable due to lack of sufficient variation in the time series of spawning biomass, and therefore the number of recruits at age 1 in year $y+1$ was modeled as a logscale mean with annual deviations

$$log(N_{1,y}) = \overline{logR} + \epsilon_y \tag{A-1}$$

where $\epsilon \sim N(0, \sigma^2)$ and R is an estimated constant recruitment. Numbers at age for the rest of the population are given by

$$N_{a,y} = N_{a-1,y-1} e^{-M_{a-1,y-1} - F_{a-1,y-1}} \qquad 1 < a < A \tag{A-2}$$

$$N_{A,y} = N_{a-1,y-1} e^{-M_{a-1,y-1} - F_{a-1,y-1}} + N_{A,y-1} e^{-M_{A,y-1} - F_{A,y-1}} \qquad a = A \tag{A-3}$$

In Eq. (A-2) and (A-3), M and F are instantaneous natural and fishing mortality rates, and in Eq. (A-3), A is the plus group, where all individuals $\geq A$ are assigned the same biological parameters. Spawning stock biomass (SSB) is calculated as

$$SSB_y = \sum_{a=1}^{A} N_{a,y} m_{a,y} w_{a,y} e^{-(M_{a,y} + F_{a,y}) \Delta t_s} \tag{A-4}$$

where $m_{a,y}$ is the probability of being mature at age a in year y, and $w_{a,y}$ is weight at age in year y. Direct measures of fecundity (eggs produced) at age by year are not available for most fish, and weight is used as a proxy instead because it is easy to measure and the data are widely available from both commercial catch and biological surveys.

Data that are fitted for Georges Bank cod include annual index values for three fishery independent surveys as well as the age composition of those surveys, and the annual total catch as well as the age composition of the catch. Predicted values are calculated as

$$\hat{I}_{i,a,y} = N_{a,y} q_i s_{i,a} e^{-(M_{a,y}+F_{a,y})\Delta t_i} \tag{A-5}$$

$$\hat{I}_{i,y} = \sum_{a=1}^{A} \hat{I}_{i,a,y} \tag{A-6}$$

$$\hat{C}_{a,y} = \frac{F_{a,y}}{M_{a,y}+F_{a,y}} N_{a,y}(1-e^{-(M_{a,y}+F_{a,y})}) \tag{A-7}$$

$$\hat{C}_y = \sum_{a=1}^{A} \hat{C}_{a,y} \tag{A-8}$$

For (A-5), $\hat{I}_{i,a,y}$ is the predicted value for survey i at age a in year y, and is calculated from the numbers at age in that year, scaled by index-specific catchability (q_i), the probability that the survey catches that age (index-specific selectivity at age, $s_{i,a}$), and then decremented for the fraction of annual mortality that occurs prior to survey timing (Δt_i). Predicted catch is simply the fraction of annual mortality at age in a given year that is due to fishing, $F_{a,y}$, which is modeled as a constant (log-scale mean) with annual deviations. Fishing mortality at a given age in a given year is the product of an instantaneous fishing mortality in a year F_y, and age-specific fishery selectivity in that year $s_{a,y}$. For Georges Bank cod, selectivity was assumed to be constant within two temporal time blocks: 1978- 1993, and 1994-2011 (Northeast Regional Stock Assessment Workshop 2013).

The index and total catch are assumed to have a lognormal distribution, with negative loglikelihood (NLL), ignoring constants, given by

$$NLL = \sum_y log(\sigma_y) + \frac{1}{2}\sum_y \frac{log(obs_y) - log(pred_y)}{\sigma_y^2} \tag{A-9}$$

Age composition data have a multinomial distribution, with NLL (again, ignoring constants)

$$NLL = -ESS \sum_\alpha p_{obs,\alpha,y} log(p_{pred,\alpha,y}) \tag{A-10}$$

In (A-9), σ_y^2 is calculated from annually specified coefficients of variation (CV_y), i.e. $\sigma^2 = log(CV^2+1)$. In (A-10), ESS is the effective sample size (a value that is input by the user), α are the ages that are included in the age composition, $p_{obs,\alpha,y}$ are the observed proportion at age, and $p_{pred,\alpha,y}$ are the predicted proportion at age.

The total objective function that is minimized is the sum of the individual negative loglikelihoods, all of which are assumed to have either lognormal (annual recruitment, annual fishing mortality, total catch, total index) or multinomial (age composition of catch, age composition of indices) distributions.

Convergence is achieved if the absolute value of the maximum gradient is less than 10^{-4}, the hessian is positive-definite, and there are no boundary solutions.

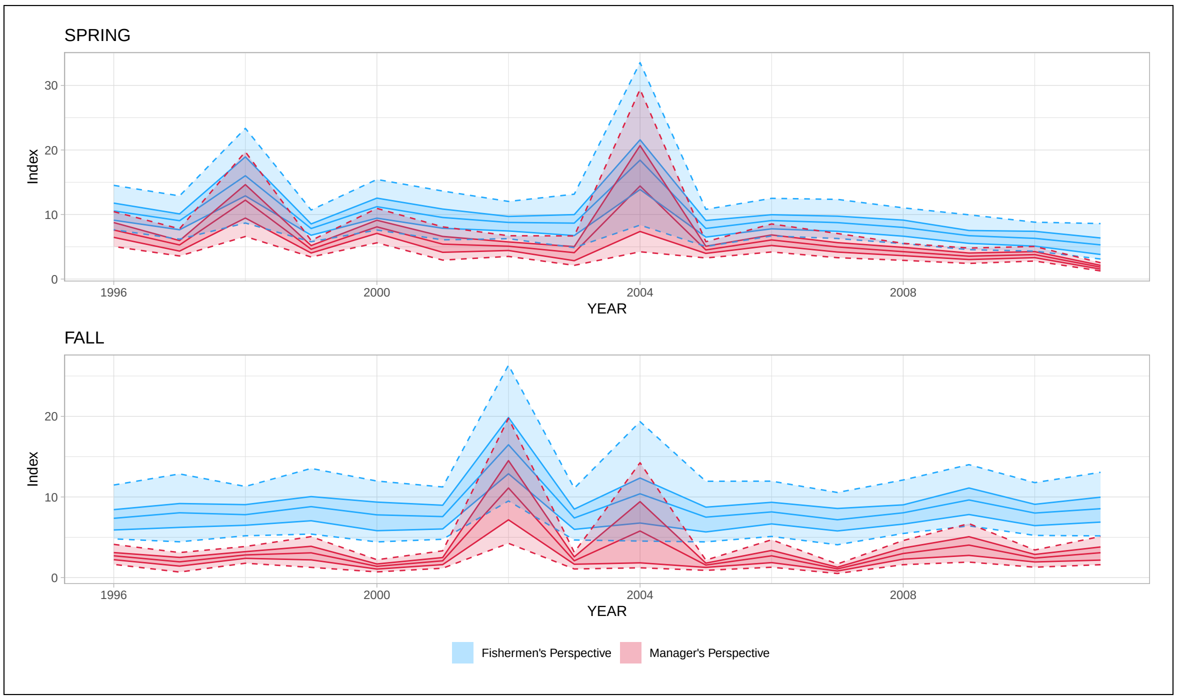

FIGURE A-1. Design based estimate of mean relative biomass (kg/tow) from the spring and fall Bottom Trawl Survey. *Manager's Perspective* is the mean relative biomass using only tows from the fishery independent survey (including zero tows), while *Fishermen's Perspective* refers to the case where zero tows were replaced with positive catch derived from the cumulative probability distribution in Figure 3. Darker shaded region is the interquartile range, lighter shading with dashed line border are the 5th and 95th percentiles.

A-2. Fishing Trip Costs

Table A-1 presents the parameter estimates of the cost model for Bottom Trawl, which is the most common gear used in the groundfish fishery. Historical estimates for the remaining gears utilized in the groundfish fishery are presented in Werner et al. (2020). A Heckman selection model is employed to estimate multi-day trip costs due to the fact that the cost data are gathered on trips carrying human observers that are deployed for bycatch estimation. The stratification for bycatch estimation generates a selection issue for cost estimation for multi-day trips. A Wald test of independent equations rejects independence for the multi-day trip ($\chi^2 = 1677.26$, p-value< 0.001) specification. To address potential collinearity issues, we employ an exclusion restriction, the natural log of number of observers employed in each month, to the selection model.

Table A-1. Bottom Trawl Trip Cost Model Estimate

	Day Trip			Multiday Trip		
Variable	Coefficient	t	p > |z|	Coefficient	z	p > |z|
Ln Cost						
Ln vessel horsepower	0.322***	14.08	0.000	0.359***	11.53	0.000
Ln vessel gross tons	0.206***	19.30	0.000	0.349***	36.19	0.000
Ln vessel age	–0.057***	-3.10	0.002	0.027	1.18	0.238
Ln hours absent	0.995***	44.74	0.000	0.926***	75.22	0.000
Ln diesel price	0.354***	7.06	0.000	0.245***	4.16	0.000
Ln average weekly wage	–0.209***	–4.61	0.000	-0.153***	-4.96	0.000
Intercept	2.282***	6.83	0.000	2.193***	9.75	0.000
Correlation of selection & outcome error terms				-0.887		
No. of uncensored obs.	13,810			11,201		
Selection (probit)						
Ln vessel horsepower				0.096**	2.11	0.035
Ln vessel gross tons				0.109***	2.77	0.006
Ln vessel age				-0.027	-1.16	0.245
Ln hours absent				0.026***	3.06	0.002

Table A-1. Bottom Trawl Trip Cost Model Estimate

	Day Trip			Multiday Trip		
Variable	Coefficient	t	p > |z|	Coefficient	z	p > |z|
Ln diesel price				0.208***	4.83	0.000
Ln average weekly wage				0.435***	4.47	0.000
Sector ID 3				-5.197***	-33.21	0.000
Sector ID 5				0.335***	12.07	0.000
Sector ID 6				0.413***	8.54	0.000
Sector ID 7				0.208***	4.88	0.000
Sector ID 9				0.252***	17.50	0.000
Sector ID 10				-0.047	-0.50	0.614
Sector ID 11				-0.400***	-5.89	0.000
Sector ID 12				0.338***	8.01	0.000
Sector ID 13				-5.007***	-53.55	0.000
Sector ID 15				0.008	0.05	0.964
Sector ID 16				0.057**	2.48	0.013
Sector ID 17				0.346***	7.41	0.000
Sector ID 18				-0.0331**	-2.46	0.014
Sector ID 19				0.027	0.32	0.75
Sector ID 20				0.3334***	6.22	0.000
Sector ID 21				-4.973***	-40.57	0.000
Sector ID 22				0.191***	3.99	0.000
Sector ID 26				0.052	0.96	0.338
Sector ID 27				0.027	0.63	0.531
Fleet 6				-0.0419	-1.14	0.254
Fleet 7				-0.140***	-2.64	0.008
Fleet 8				0.242***	9.49	0.000
Fleet 10				-4.934***	-43.38	0.000
Fleet 11				-5.085***	-52.18	0.000
Fleet 12				-0.396***	-4.22	0.000
Fleet 13				-4.868***	-45.37	0.000

Table A-1. Bottom Trawl Trip Cost Model Estimate

Variable	Day Trip Coefficient	t	p > |z|	Multiday Trip Coefficient	z	p > |z|
Fleet 14				-5.017***	-33.23	0.000
Fleet 15				-5.081***	-43.19	0.000
Fleet 16				-0.425***	-9.7	0.000
Fleet 19				-4.986***	-42.39	0.000
Fleet 20				0.121***	6.06	0.000
Fleet 21				0.228**	1.99	0.047
Fleet 23				-4.668***	-26.44	0.000
Fleet 24				0.452**	2.05	0.040
Fleet 25				-4.820***	-43.11	0.000
Fleet 27				-0.031	-0.35	0.729
Fleet 28				0.323***	8.94	0.000
Fleet 29				-5.184***	-28.62	0.000
Fleet 31				-4.940***	-48.29	0.000
Fleet 32				-1.164***	-3.34	0.000
Fleet 35				-5.193***	-51.69	0.000
Fleet 38				-0.035	-0.88	0.378
Fleet 41				-5.179***	-35.64	0.000
Fleet 42				0.171	1.17	0.244
Fleet 56				-5.206***	-50.81	0.000
Fleet 60				0.105**	2.00	0.046
Fleet 62				0.553***	4.45	0.000
Fleet 66				-4.814***	-26.66	0.000
Fleet 75				-5.232***	-43.24	0.000
Fleet 80				-0.5084***	-5.39	0.000
Fleet 82				0.084	0.37	0.711
Fleet 85				0.258	1.24	0.217
Fleet 86				-4.854***	-46.75	0.000
Fleet 92				-0.137***	-5.37	0.000

Table A-1. Bottom Trawl Trip Cost Model Estimate

	Day Trip			Multiday Trip		
Variable	Coefficient	t	p > |z|	Coefficient	z	p > |z|
Ln no. of observers				0.341***	8.14	0.000
Intercept				-7.154***	-9.44	0.000
Correlation of selection & outcome error terms				-0.887		
No. of censored obs.				75,255		
Total obs.				86,456		

The model includes seasonal (quarterly) and year fixed effects.

A-3. The Largest Fishing Businesses

Table A-2. Three-Year Net Present Value for the three largest fishing businesses under different discount rates (millions of dollars).

Simulation	Discount Rate	Mean	Median	Std. Dev.	Min	Max
Fishermen's Perspective	0.020	\$48	\$46	\$15	\$14	\$124
Manager's Perspective	0.020	\$28	\$26	\$10	\$3	\$89
Manager's Perspective w/ Depletion	0.020	\$47	\$46	\$8	\$13	\$77
Fishermen's Perspective	0.070	\$43	\$42	\$14	\$13	\$113
Manager's Perspective	0.070	\$25	\$24	\$9	\$3	\$81
Manager's Perspective w/ Depletion	0.070	\$42	\$41	\$7	\$13	\$70
Fishermen's Perspective	0.116	\$40	\$38	\$13	\$12	\$104
Manager's Perspective	0.116	\$23	\$22	\$8	\$2	\$75
Manager's Perspective w/ Depletion	0.116	\$39	\$38	\$7	\$12	\$64

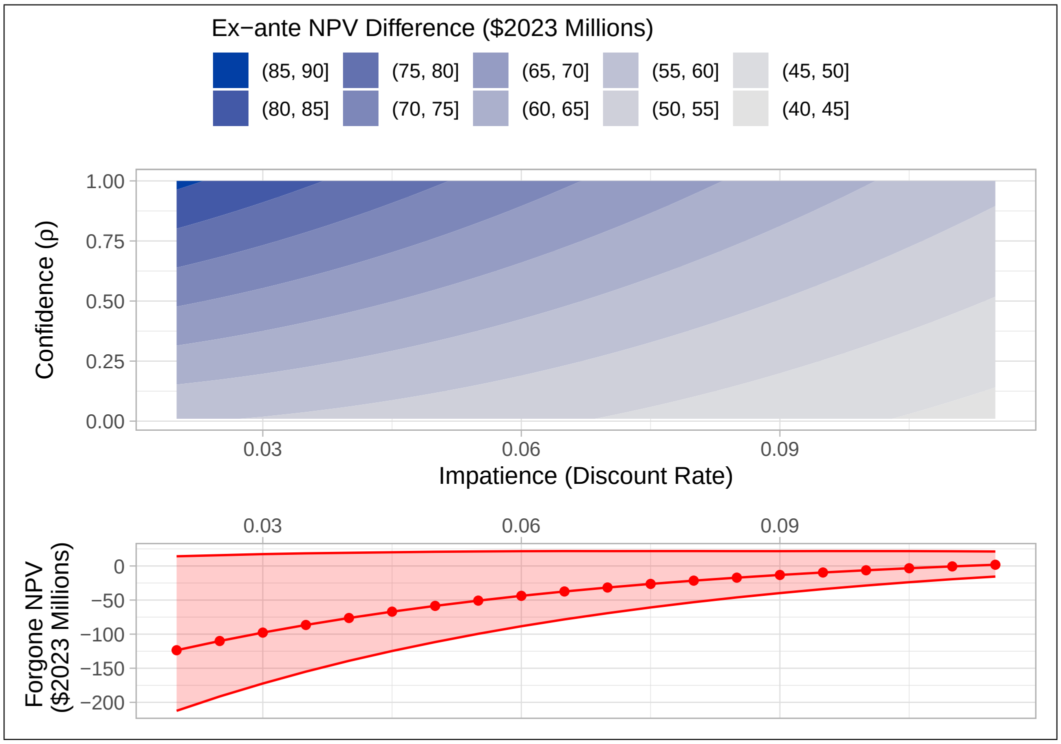

Figure A-2. Top panel: for the largest three businesses, difference between NPV calculated using weighted flows from the *Fishermen's Perspective* and *Manager's Perspective with Depletion* scenarios and NPV from the *Manager's Perspective* scenario for varying discount rates and initial confidence in a Fishermen's own beliefs over the science (ρ). That initial ρ is updated over time as harvesters receive signals on profitability (i.e., based on differences in net revenue under the *Fishermen's Perspective* and *Manager's Perspective with Depletion* scenarios). Bottom panel: mean and 95% confidence interval for the foregone (discounted) net revenue the industry would have earned over the period 2013-2030 if it had accepted the *Manager's Perspective* and not engaged in lobbying.