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The Design and Implementation of Index Insurance in Fisheries

A dissertation submitted in partial satisfaction
of the requirements for the degree

Doctor of Philosophy
in
Environmental Science and Management

by

Nathaniel Gordon Grimes

Committee in charge:

Professor Christopher Costello, Chair
Professor Andrew Plantinga
Professor Steve Gaines

June 2026

The Dissertation of Nathaniel Gordon Grimes is approved.

Professor Andrew Plantinga

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Professor Christopher Costello, Committee Chair

June 2026

The Design and Implementation of Index Insurance in Fisheries

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by

Nathaniel Gordon Grimes

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Curriculum Vitæ

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Abstract

The Design and Implementation of Index Insurance in Fisheries

by

Nathaniel Gordon Grimes

Environmental shocks, such as marine heatwaves and harmful algal blooms, greatly damage fishing communities. Fishers have limited access to financial tools to ameliorate income loss due to diminished fishery productivity. Index insurance is a promising new tool to help protect fishers during environmental downturns. However, designing effective index insurance contracts for fisheries presents distinct and unresolved challenges. Unique fishery characteristics such as vulnerability to overexploitation, complex environmental to harvest relationships, and interaction with management have stymied deployment. This dissertation addresses each of the limitations in three chapters to enable effective and sustainable use of index insurance in fisheries.

Chapter one models fisher behavior changes induced through insurance moral hazard. My results show standard fishery production models in unconstrained settings lead insurance to incentivize increased harvest. Insurance will not be viable in the long run if it leads to overexploited stocks. Insurance may reduce harvest if fishers possess more adaptive risk mitigation strategies than standard model assumptions. Using estimates from Norwegian fisheries, index insurance may reduce harvest by 2% or increase harvest by as much as 20% depending on the type of insurance contract, risk characteristics of harvest, and fisher risk aversion.

Chapter two compares multivariate contracts built through machine learning algorithms with univariate contracts built through standard linear regression, using the California Market Squid fishery as a case study. Only one of twelve single-index contracts

was viable in a private market, compared to three of four machine learning contracts. Community welfare would have improved had contracts built through machine learning been available over the past decade.

Chapter three examines how fisher decisions on insurance coverage influence management decisions on quota allocations. If management sufficiently mitigates risk exposure, fishers may not need insurance. Yet management decisions can harm fishing communities in the short run while protecting the long run — a gap index insurance can fill. Using stochastic dynamic optimization, I find that managers face two countervailing incentives when fishers have access to private insurance. Numerical results show these behavioral changes are modest, and only subsidized insurance meaningfully alters optimal harvest control rules.

This dissertation demonstrates that index insurance has the potential to promote climate resilient fisheries when combined with effective management and cutting edge data science to build good contracts.

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Chapter 1

The Behavioral Effects of Index Insurance in Fisheries

1.1 Introduction

Fisheries face significant environmental risks that threaten biological and economic sustainability, yet financial tools to protect fishing communities from these risks remain limited (Alvarez *et al.*, 2006; Lehodey *et al.*, 2006; Rogers *et al.*, 2019; Cheung *et al.*, 2021; Oken *et al.*, 2021; Smith *et al.*, 2023; Sethi, 2010; Kasperski and Holland, 2013). Index insurance is a new financial tool that has significant potential to stabilize community income in response to disastrous weather events (Maltby *et al.*, 2023; Watson *et al.*, 2023; Hobday *et al.*, 2025). However, insurance possesses moral hazards that may induce behavior change in fishers. In this paper, we provide the first examination of whether index insurance will increase or decrease fishery harvest. This is important topic of investigation because many fisheries worldwide remain vulnerable to overfishing (FAO, 2020). We apply our theoretical findings to an empirical setting in three Norwegian fisheries.

Fishers are highly sensitive to risk, especially income risk, and demonstrate risk aversion despite working a seemingly risky profession (Smith and Wilen, 2005; Holland, 2008; Sethi, 2010). Choices by fishers and fishery managers mitigate environmental risk. Individual efforts include choosing consistent, known fishing grounds over risking exploring unknown spots (Holland, 2008) or choosing to fish less after storms and hurricanes Pfeiffer (2020); Pfeiffer *et al.* (2022). However, these efforts are unlikely to completely eliminate risk. Additional financial tools may be needed to address income risk for fishers as a result of environmental fluctuations (Sethi, 2010; Kasperski and Holland, 2013; Wabnitz and Blasiak, 2019; Sumaila *et al.*, 2021).

Index insurance may be an ideal financial tool for risk management in fisheries as it is scalable, protects against environmental shocks, and smooths income for fishers (Watson *et al.*, 2023; Hobday *et al.*, 2025). Index insurance uses independent measures of weather as the basis for issuing payouts to all policyholders. For example, a pilot program through the Caribbean Oceans and Aquaculture Sustainability Facility (COAST) pays out a set amount to fishers when indices of wave height, wind speed, and storm surge indicate a hurricane (Sainsbury *et al.*, 2019).

One crucial area that remains under studied is the potential influence of insurance on fisher behavior. Moral hazards are decisions by insured agents that they would not otherwise take if they were uninsured Wu *et al.* (2020). There are two components to insurance moral hazards: “chasing the trigger” and “risk reduction”. “Chasing the trigger” is the directed behavior of policyholders to increase the likelihood of a payout. For example, a fisher might choose to fish less to receive an indemnified harvest insurance payment. Index insurance completely eliminates this moral hazard as the index is independent of fisher choices, e.g. fishers cannot affect sea surface temperature. “Risk reduction” occurs when policyholders possess an insurance contract that protects them from risk, leading them to reoptimize their decisions. Index insurance remains susceptible to this element

of moral hazard. One possible response by fishers is to take on additional risk by fishing more. Alternatively, the risk protection offered by insurance could encourage fishers to fish less as insurance payouts sufficiently cover income loss. All preliminary analyses of fisheries index insurance are missing rigorous assessment of risk reduction moral hazards.

The current working assumption by practitioners is that index insurance will motivate fishers to fish less by relieving income constraints, but there is no evidence beyond anecdotes (RARE, 2021). Previous studies articulated hypothetical examples of moral hazards in potential fishery indemnity insurance programs, such as encouraging fishers to fish in foul weather or to not exit the fishery after a bad year of harvest (Herrmann *et al.*, 2004; Watson *et al.*, 2023). However, neither study built testable models to uncover risk reduction moral hazard impacts on fisheries.

Research from agriculture provides compelling evidence that behavior change ought to be expected in fisheries. Index insurance applied to grazing in pasture commons shows clear evidence of risk reduction moral hazards leading to environmental degradation (Müller *et al.*, 2011; Bulte and Haagsma, 2021). Other studies from agriculture find that the impact of insurance on environmental sustainability depends on the underlying risk reducing or increasing qualities of inputs used in production (Ramaswami, 1993; Mahul, 2001; Mishra *et al.*, 2005). Risk increasing (decreasing) inputs will always lead to increased (decreased) input use with insurance. Numerous agricultural studies confirm insurance incentivizes changes in input use (Horowitz and Lichtenberg, 1993; Babcock and Hennessy, 1996; Smith and Goodwin, 1996; Mishra *et al.*, 2005; Cai, 2016; Deryugina and Konar, 2017; Claassen *et al.*, 2017; Elabed and Carter, 2018; Sibiko and Qaim, 2020; Stoeffler *et al.*, 2022; Sloggy *et al.*, 2025).

Fisheries differ from agriculture in crucial ways, thus motivating an analysis of the behavioral effects of index insurance in this new setting. In a standard fisheries model, production by a fisher depends on the abundance of the resource, as measured by the fish

stock. In this case, there is a positive relationship between output and inputs of labor and capital. For example, more fishing boats results in a greater catch for a given fish stock. When the fish stock is subject to stochastic shocks, inputs will be risk-increasing and, thus, index insurance covering biological stock risk will always increase input use and harvest of the resource. This suggests that index insurance will be in conflict with conservation goals in fisheries. However, fishers also face risk that is independent of biological risk. For example, weather and wave conditions may make it difficult to catch fish or new regulations may limit where fishing can take place. Inputs that interact with extraction shocks may be risk-increasing or risk-decreasing. Therefore, index insurance applied to extraction risk has the potential to reduce harvest and conserve fish stocks. A complete analysis of index insurance in fisheries is needed to understand the different types of risk faced by fishers, alternative ways in which insurance contracts can be designed, and whether insurance will be compatible with conservation goals.

The remainder of the paper is structured as follows. Section 1.2 demonstrates that in a standard fishery production model, index insurance will always result in greater harvest. We then present a new stochastic production function for fisheries that integrates both stock and extraction risk in Section 1.3. Fishers now face multiple risks where contracts could be specified to protect either risk. In this new setting, we prove how index insurance will change fisher behavior, and how the outcome depends on the risk effects of inputs as well as the type of insurance contract. Section 1.4 extends the theoretical model to account for multiple inputs in fishing that reflects the decisions of fishers in the empirical setting. Section 1.5 numerically estimates potential harvest changes with an index insurance program. Parameters are calibrated with an application to Norwegian fisheries through the results of Asche *et al.* (2020). The Norwegian fisheries show index insurance could raise harvest by 20% or lower harvest by 2% contingent on the fishery input characteristics and contract type. All contracts specified to protect biological stock

risk showed large increases in harvest regardless of the extraction risk effects. Currently, most proposed insurance contracts are examining triggers based on stock risk, such as sea surface temperature or chlorophyll-a (Watson *et al.*, 2023). Without additional constraints, these types of contracts will incentivize greater exploitation of vulnerable fish stocks. Section 1.6 concludes with a discussion on the suitability of fishery index insurance.

1.2 Index Insurance with standard fishery production

Here we develop a model of fishery production under risk. We are primarily interested in within-season input decisions and risk, so we omit time subscripts, but will be explicit about when random variables are known, or unknown, to fishers. We also omit fishery management, treating the fishery as unregulated so that fishers face no constraints on their choices. This is a useful simplification because the core incentives driving fisher behavior in an unregulated setting persist under most management regimes. We begin with a canonical model of fishery production.

Fishers choose an input x that interact through an increasing concave production technology $f(x)$ ¹. Fish biomass is B , and total production, or “harvest”, y is given by:

$$y = Bf(x) \tag{1.1}$$

We assume that B is unknown prior to the choice of x , but that some information on B is available. Specifically, we assume $B = \hat{B} + \theta$, where $\hat{B}$ is known and θ is mean zero additive error term, with known variance σ_θ^2 ; we will refer to θ as the “stock risk”. This implies that Equation 1.1 can be rewritten:

¹Common specifications of $f(x)$ are Cobb-Douglas or linear harvest from Gordon-Schaefer.

$$y = \hat{B}f(x) + \theta f(x) \quad (1.2)$$

This approach combines a standard model of fishery production (Equation 1.1) with the simple observation that biomass, which affects harvest, is unknown prior to the choice of inputs. With this model, we can examine how index insurance affects incentives around input choice. Under standard assumptions: fishers are price takers, incur convex costs, and are risk averse over profits. We define a simple profit function where prices are normalized to one:

$$\pi = \hat{B}f(x) + \theta f(x) - c(x) \quad (1.3)$$

We create an insurance lottery through a contract that uses θ as the index. The trigger $\bar{\theta}$ initiates a constant payout γ when the index falls below the trigger, $\theta < \bar{\theta}$. Actuarially fair insurance implies the premium, ρ , paid in both lottery outcomes to be the probability of receiving a payout times the payout amount, $\rho = J(\bar{\theta})\gamma$, where $J(\theta)$ is the cumulative distribution of the shock. Additionally, if we set the trigger to zero, $\bar{\theta} = 0$, profit will enter corresponding bad and good states when θ is positive and negative, respectively.

Fishers are expected utility maximizers. To do so, they need to make decisions on the marginal profitability in the good and bad states. We introduce the following lemma to help us compare marginal profits in both states:

Lemma 1.2.1 *Index insurance contracts built on θ will always lead to higher expected marginal profits in the good state:*

$$\frac{\mathbb{E}[\partial\pi|\theta < \bar{\theta}]}{\partial x} - \frac{\mathbb{E}[\partial\pi|\theta > \bar{\theta}]}{\partial x} < 0$$

The proof of Lemma 1.2.1 is included in the appendix.

Risk aversion is a necessary condition for insurance to be desirable (François Outreville, 2014). Therefore, we assume fishers are risk averse to income shocks through an increasing, concave utility function where $u' > 0$ and $u'' < 0$. Fishers will maximize their own expected utility in the lottery by choosing the input given an exogenous insurance contract:

$$U \equiv \max_x \mathbb{E}[U] = \int_{-\infty}^{\bar{\theta}} j(\theta) u(\pi(x, \hat{B}, \theta) + (1 - J(\bar{\theta}))\gamma) d\theta + \int_{\bar{\theta}}^{\infty} j(\theta) u(\pi(x, \hat{B}, \theta) - J(\bar{\theta})\gamma) d\theta \quad (1.4)$$

The first order condition that solves Equation 1.4 is then:

$$\begin{aligned} \frac{\partial U}{\partial x} &= \int_{-\infty}^{\bar{\theta}} j(\theta) u_x(\pi(x, \hat{B}, \theta) + (1 - J(\bar{\theta}))\gamma) \frac{\partial \pi}{\partial x}(x, \hat{B}, \theta) d\theta \\ &\quad + \int_{\bar{\theta}}^{\infty} j(\theta) u_x(\pi(x, \hat{B}, \theta) - J(\bar{\theta})\gamma) \frac{\partial \pi}{\partial x}(x, \hat{B}, \theta) d\theta \\ &= 0 \end{aligned} \quad (1.5)$$

To find the effect of insurance on optimal input choice, we use the implicit function theorem to examine how input choice varies with the insurance payout γ :

$$\frac{\partial x^*}{\partial \gamma} = - \frac{\frac{\partial U}{\partial x \partial \gamma}}{\frac{\partial^2 U}{\partial x^2}} \quad (1.6)$$

We use γ to test insurance effects, because a marginal change in the payout increases the value of insurance². Receiving more compensation in the bad states provides greater boosts to utility for risk averse fishers.

By the sufficient condition of a maximization problem, $\frac{\partial^2 U}{\partial x^2}$ is negative so we can focus

²As shown in the appendix, marginal utility reaches a maximum value before decreasing at high γ . Therefore we assume the change in γ occurs in regions of increasing marginal utility in γ for simplicity, but our proof will hold for any γ .

solely on the numerator to sign the effect. The numerator of Equation 1.6 is given by:

$$\begin{aligned} \frac{\partial^2 U}{\partial x \partial \gamma} = & \int_{-\infty}^{\bar{\theta}} j(\theta) u''(\pi(x, \hat{B}, \theta) + (1 - J(\bar{\theta}))\gamma) \frac{\partial \pi}{\partial x}(x, \hat{B}, \theta) (1 - J(\bar{\theta})) d\theta \\ & + \int_{\bar{\theta}}^{\infty} j(\theta) u''(\pi(x, \hat{B}, \theta) - J(\bar{\theta})\gamma) \frac{\partial \pi}{\partial x}(x, \hat{B}, \theta) (-J(\bar{\theta})) d\theta \end{aligned} \quad (1.7)$$

Proposition 1.2.1 *For insurance contracts specified at trigger $\bar{\theta} = 0$ with production function $y = \hat{B}f(x) + \theta f(x)$, optimal harvest will always increase with an increase in γ .*

Proof: Suppose insurance fully covers the loss between states, then utility in the good state and bad state are equal to each other so that we can factor out like terms in Equation 1.7. For brevity, all like terms including γ are indicated by $u(\cdot)$.

$$\begin{aligned} \frac{\partial^2 U}{\partial x \partial \gamma} = & J(\bar{\theta})(1 - J(\bar{\theta}))u''(\cdot) \\ & \times \left[\int_{-\infty}^{\bar{\theta}} j(\theta) \frac{\partial \pi}{\partial x}(x, \hat{B}, \theta) d\theta - \int_{\bar{\theta}}^{\infty} j(\theta) \frac{\partial \pi}{\partial x}(x, \hat{B}, \theta) d\theta \right] \end{aligned} \quad (1.8)$$

The first term of Equation 1.8 is negative by the concavity of utility, $u''(\cdot) < 0$. The second term of Equation 1.8 is negative by Lemma 1.2.1.

Therefore, an index insurance contract built assuming a standard fishery production model will always lead to increased input use, and thus more harvest. ■

Fishers will choose an insurance contract that maximizes their expected utility without market constraints. There could be market distortions such as subsidies or limits on coverage that may prevent fishers from choosing the optimal level. Regardless of the level of insurance payouts, fishers will always increase input use by Proposition 1.2.1.

Proposition 1.2.1 immediately challenges the sustainability of index insurance in fisheries. Insurance may protect fishers in the short run from environmental shocks and encourage fishers to expand production, but the resulting increase in harvest will under-

mines long run biological sustainability. However, this result may be a structural artifact of the standard production models widely used in fisheries. Inputs in these models are inherently "risk increasing", where adding more of an input raises average production, but also its variance ³. A similar phenomenon was observed in agriculture where the assumption of standard production models often failed to reflect realized harvest or risk taking strategies by farmers (Just and Pope, 1978). Just and Pope (1979) suggested a more flexible specification of production functions where inputs could either increase or decrease risk depending on their "risk effects". A robust literature then identified that risk effects are the primary determinants of how insurance influences farmers input choices (Ramaswami, 1993; Mahul, 2001; Horowitz and Lichtenberg, 1993; Babcock and Hennessy, 1996; Smith and Goodwin, 1996). Index insurance always raises the use of risk increasing inputs and lowers the use of risk decreasing inputs. The finding from Proposition 1.2.1 therefore follows directly from the assumption that all inputs in a standard fishery model are risk increasing, an assumption worth relaxing.

Fishers are exposed to more margins of risk and possess means to mitigate those risks beyond ways captured in the simple canonical model. In the next section we extend the fishery production framework to incorporate sources of risk unique to fisheries and allow for flexible input risk effects, better reflecting the risk mitigation strategies fishers actually use.

1.3 Index insurance with risky fishery production

Anecdotally and empirically, fishers make informed decisions to mitigate risk beyond just exposure to stock risk (Kirkley and Strand, 1998; Eggert and Tveteras, 2004; Kompas *et al.*, 2004; Smith and Wilen, 2005; Sethi, 2010; Holland, 2008; Pfeiffer, 2020; Pfeiffer

³Note that: $V(y) = \sigma^2 f(x)^2$, the derivative is always positive because $\frac{f(x)}{\partial x} > 0$: $\frac{\partial V(y)}{\partial x} = 2\sigma^2 \frac{\partial f(x)}{\partial x}$

et al., 2022). Stock risk, θ , remains an inevitable source of risk that we must maintain in any fishery model, but we expand the standard fishery model in Equation 1.2 adding a second source of risk called extraction risk:

$$y = \hat{B}f(x) + \theta f(x) + \omega h(x) \quad (1.9)$$

All other forms of risk not captured by stock risk are extraction risk, ω , where ω is a random variable unknown to fishers before they choose inputs with $\mathbb{E}[\omega] = 0$ and variance σ_ω^2 . Foul weather, regulatory changes, or inherent variability in extraction all impact fisher production. Fisher inputs may interact with these risks through the extraction risk effect function $h(x)$. Extraction risk effects may reduce or increase risk. Inputs that increase variance are called risk increasing, $h_x(x) > 0$, and inputs that decrease variance are called risk decreasing, $h_x(x) < 0$ (Just and Pope, 1978).

We will refer to production in the form of Equation 1.9 as “risky production”. Risky production is more flexible than the standard fishery production model in Equation 1.2 as it allows for two sources of risk and multiple avenues for fishers to mitigate risk. Risky production nests the standard fishery production model as a special case when $\omega = 0$ or $h(x) = 0$. It also maintains increasing mean production in inputs so that changes in inputs correspond to changes in expected harvest.

With two sources of risk and adaptive margins, we have created a more nuanced representation of risky production in fisheries. However, it is not immediately clear how index insurance will affect fisher harvest decisions with Equation 1.9. We can amend the insurance framework from Section 1.2 to assess the potential behavioral implications of an insurance contract to protect against stock, θ , or extraction risk, ω . Profits with risky production update Equation 1.3:

$$\pi = \hat{B}f(x) + \theta f(x) + \omega h(x) - c(x) \quad (1.10)$$

We assume fishers and insurance companies have perfect information on both distributions of random variables. Therefore, we create insurance lotteries through contracts that use either ω or θ as the trigger. For notational ease, we present the model with a contract built on ω , but the structure is interchangeable with contracts built on θ . By allowing contracts on only one of the random variables, we introduce basis risk as a contract triggered solely on ω cannot protect against all the biological risk of θ . We assume that θ and ω are independent⁴. An example of how shocks could be independent is that stock shocks operate at different time scales than extraction shocks (Alvarez *et al.*, 2006).

Payouts remain a constant γ and fishers pay a premium, $\rho = J((\bar{\omega})\gamma)$, in both states. As before, the marginal profits in both states are crucial to understanding fisher behavior. For contracts built on ω the risk effects function $h(x)$ is critical. We introduce the following lemma to help us compare marginal profits in both states:

Lemma 1.3.1 *Expected marginal profit is higher in bad states for risk decreasing inputs when insurance contracts are built on extraction risk ω :*

$$\frac{\mathbb{E}[\partial\pi|\omega < \bar{\omega}]}{\partial x} - \frac{\mathbb{E}[\partial\pi|\omega > \bar{\omega}]}{\partial x} > 0 \text{ if } h_x(x) < 0$$

Otherwise, risk increasing inputs lead to higher expected marginal profit in the good states:

$$\frac{\mathbb{E}[\partial\pi|\omega < \bar{\omega}]}{\partial x} - \frac{\mathbb{E}[\partial\pi|\omega > \bar{\omega}]}{\partial x} < 0 \text{ if } h_x(x) > 0$$

⁴In the appendix we include proofs when shocks are perfectly correlated, but the results become difficult to extract clear insights

The proof of Lemma 1.3.1 is included in the appendix. The results of Lemma 1.2.1 hold even with risky production in Equation 1.9 as shown in the proof of Lemma 1.2.1.

Fishers consider the joint distribution $j(\omega, \theta)$ of shocks to maximize their utility with exogenous insurance contracts:

$$U \equiv \max_x \mathbb{E}[U] = \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\bar{\omega}} j(\omega, \theta) u(\pi(x, \hat{B}, \theta, \omega) + (1 - J(\bar{\omega}))\gamma) d\omega + \int_{\bar{\omega}}^{\infty} j(\omega, \theta) u(\pi(x, \hat{B}, \theta, \omega) - J(\bar{\omega})\gamma) d\omega \right] d\theta \quad (1.11)$$

The first order condition that solves Equation 1.11 is then:

$$\begin{aligned} \frac{\partial U}{\partial x} = \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\bar{\omega}} j(\omega, \theta) u_x \left(\pi(x, \hat{B}, \theta, \omega) + (1 - J(\bar{\omega}))\gamma \right) \right. \\ \times \frac{\partial \pi}{\partial x}(x, \hat{B}, \theta, \omega) d\omega \\ + \int_{\bar{\omega}}^{\infty} j(\omega, \theta) u_x \left(\pi(x, \hat{B}, \theta, \omega) - J(\bar{\omega})\gamma \right) \\ \times \frac{\partial \pi}{\partial x}(x, \hat{B}, \theta, \omega) d\omega \left. \right] d\theta = 0. \end{aligned} \quad (1.12)$$

Changes in optimal inputs due to insurance are characterized by the Implicit Function Theorem, as in Equation 1.6, but now the numerator is given by:

$$\begin{aligned} \frac{\partial^2 U}{\partial x \partial \gamma} = \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\bar{\omega}} j(\omega, \theta) u'' \left(\pi(x, \hat{B}, \theta, \omega) + (1 - J(\bar{\omega}))\gamma \right) \right. \\ \times \frac{\partial \pi}{\partial x}(x, \hat{B}, \theta, \omega) (1 - J(\bar{\omega})) d\omega \\ + \int_{\bar{\omega}}^{\infty} j(\omega, \theta) u'' \left(\pi(x, \hat{B}, \theta, \omega) - J(\bar{\omega})\gamma \right) \\ \times \frac{\partial \pi}{\partial x}(x, \hat{B}, \theta, \omega) (-J(\bar{\omega})) d\omega \left. \right] d\theta. \end{aligned} \quad (1.13)$$

We examine input decisions with insurance contingent on the source of risk the insurance

is designed to protect. Proposition 1.3.1 demonstrates that contracts built on extraction risks depend on the underlying input risk effects.

Proposition 1.3.1 *For index insurance contracts specified at trigger $\bar{\omega} = 0$, optimal fisher harvest will decrease with an increase in γ when $h_x(x) < 0$ and increase when $h_x(x) > 0$.*

Proof: Independence of ω and θ allows us to factor out the joint distribution in the integral of Equation 1.13 into the respective marginal distributions given by $j_\theta(\theta)$ and $j_\omega(\omega)$ respectively:

$$\begin{aligned} \frac{\partial^2 U}{\partial x \partial \gamma} = & \int_{-\infty}^{\infty} j_\theta(\theta) \left[\int_{-\infty}^{\bar{\omega}} j_\omega(\omega) u''(\pi(x, \hat{B}, \theta, \omega) + (1 - J(\bar{\omega}))\gamma) \right. \\ & \times \frac{\partial \pi}{\partial x}(x, \hat{B}, \theta, \omega) (1 - J(\bar{\omega})) d\omega \\ & + \int_{\bar{\omega}}^{\infty} j_\omega(\omega) u''(\pi(x, \hat{B}, \theta, \omega) - J(\bar{\omega})\gamma) \\ & \times \frac{\partial \pi}{\partial x}(x, \hat{B}, \theta, \omega) (-J(\bar{\omega})) d\omega \left. \right] d\theta. \end{aligned} \quad (1.14)$$

If insurance fully covers the loss between states, then utility in the good state and bad state are equal to each other so that we can factor out like terms in Equation 1.14. For brevity, all like terms including γ are indicated by $u(\cdot)$:

$$\begin{aligned} \frac{\partial^2 U}{\partial x \partial \gamma} = & \int_{-\infty}^{\infty} j_\theta(\theta) J(\bar{\omega})(1 - J(\bar{\omega})) u''(\theta, \cdot) \\ & \times \left[\int_{-\infty}^{\bar{\omega}} j_\omega(\omega) \frac{\partial \pi}{\partial x}(x, \hat{B}, \theta, \omega) d\omega \right. \\ & \left. - \int_{\bar{\omega}}^{\infty} j_\omega(\omega) \frac{\partial \pi}{\partial x}(x, \hat{B}, \theta, \omega) d\omega \right] d\theta. \end{aligned} \quad (1.15)$$

The first term outside the brackets is negative by the definition of concave utility, $u'' < 0$. Lemma 1.3.1 demonstrates the interior of the brackets is positive when $h_x(x) < 0$

as the marginal profit in the bad state is greater than the marginal profit in the good. Therefore, index insurance will decrease input use for risk decreasing inputs when the extraction shocks are independent of stock shocks. When $h_x(x) > 0$, the interior sign of the brackets in Equation 1.15 is negative by Lemma 1.3.1. Therefore, index insurance will increase input use for risk increasing inputs. The direction of input change will exactly match the direction of harvest change by the properties of the production function. ■

Proposition 1.3.1 shows contracts specified on extraction risk could have positive or negative effects on harvest depending on the risk effects of the input. Insurance lowers the use of risk decreasing inputs because the need to protect against risk with that input is replaced by the risk mitigating qualities of insurance. Insurance increases risk increasing inputs as it protects against additional risk allowing fishers to expand production without taking on greater risk. The stock risk persists when contracts are specified on extraction risks, but is not influential in the marginal decision with insurance. Instead, if we specify a contract on the stock shocks, then the stock risk effects on harvest are unambiguous as stated in the following proposition:

Proposition 1.3.2 *For index insurance contracts specified at trigger $\bar{\theta} = 0$, optimal harvest will always increase with an increase in γ .*

Proof: A contract built with θ will follow the same steps as the proof for Proposition 1.3.1 with the only difference being in the integral bounds and the differential variables:

$$\begin{aligned} \frac{\partial^2 U}{\partial x \partial \gamma} &= \int_{-\infty}^{\infty} j_{\omega}(\omega) J(\bar{\theta})(1 - J(\bar{\theta})) u''(\omega, \cdot) \\ &\quad \times \left[\int_{-\infty}^{\bar{\theta}} j_{\theta}(\theta) \frac{\partial \pi}{\partial x}(x, \hat{B}, \theta, \omega) d\theta \right. \\ &\quad \left. - \int_{\bar{\theta}}^{\infty} j_{\theta}(\theta) \frac{\partial \pi}{\partial x}(x, \hat{B}, \theta, \omega) d\theta \right] d\omega. \end{aligned} \tag{1.16}$$

The 2nd term of Equation 1.16 is always negative by Lemma 1.2.1. Therefore, a contract built on θ will always increase optimal input use. ■

Proposition 1.3.2 demonstrates a clear bias towards increased fishing with contracts solely specified on θ . Increased stock abundance directly leads to higher variance. Insurance only protects against the additional stock risk, and encourages fishers to expand production. Fishers have no means to lower stock risk through input choices.

1.4 Insurance with multiple inputs

The single input model provides clear, testable insights. However, real world fisheries are more complex than single input models. We develop a multi-input model to represent this complexity. The multi-input model provides the foundation of our numerical analysis that leverages parameter estimations from Asche *et al.* (2020). Their study estimated production and risk effect parameters across three inputs in Norwegian fisheries. The numerical analysis will allow us to quantify the directional effects of insurance on fisher behavior for valuable Norwegian fisheries.

We extend the model of the previous section to two inputs, $X \in \{x_a, x_b\}$. Two inputs sufficiently articulate the complexities that arise while still remaining tractable to solve. There are two additional effects to consider when adding more inputs. The interaction between inputs leads to the first effect. Changes in input use may not correspond to the direction dictated by their respective extraction risk effects. For example, a fisher may not choose to reduce a risk decreasing input if the cross partial effects of production and risk negatively impact production of another input. We summarize the conditions that lead to unequivocal changes in input use in Proposition 1.4.1.

Proposition 1.4.1 *In fisheries with two inputs, index insurance specified with contracts on ω will increase (decrease) the optimal use of a specific input if the input's risk effects*

are increasing (decreasing) when the following sufficient condition is true:

$\frac{\partial^2 U}{\partial x_a \partial x_b} > 0$ when both inputs share the same risk effects, and $\frac{\partial^2 U}{\partial x_a \partial x_b} < 0$ when inputs have opposite risk effects.

Otherwise, index insurance may lead to ambiguous changes in the input regardless of the input's own risk effect.

The proof is included in Section A.1.3.

The second effect is a straightforward consequence of adding inputs. While insurance may incentivize greater use of one input, it may simultaneously reduce use of another. The net change in harvest depends on both the magnitude of adjustment in each input and their relative production elasticities, as stated in the following proposition:

Proposition 1.4.2 *When index insurance leads to increases (decreases) of both inputs, total expected harvest will increase (decrease). Otherwise, the total change in expected harvest depends on the relative change in input use and $\frac{\partial f(x_m)}{\partial x_m}$ where $m \in \{a, b\}$*

Proof: The total derivative of expected harvest is:

$$d\mathbb{E}[y] = \hat{B} \frac{\partial f(x_a, x_b)}{\partial x_a} dx_a + \hat{B} \frac{\partial f(x_a, x_b)}{\partial x_b} dx_b \quad (1.17)$$

Marginal production is positive, therefore $\frac{\partial f(x_m)}{\partial x_m} > 0$ for either input represented by x_m . When $dx_a > 0$ and $dx_b > 0$, Equation 1.17 is always positive. The opposite is true when $dx_a < 0$ and $dx_b < 0$.

For inputs with changes in opposite directions, Equation 1.17 is positive or negative depending on the relative sizes of $\frac{\partial f(x_a, x_b)}{\partial x_a} dx_a$ and $\frac{\partial f(x_a, x_b)}{\partial x_b} dx_b$ ■

Proposition 1.4.2 shows that reductions in certain inputs may be offset by subsequent increases in more productive ones. In other words, lowering one margin of production through insurance does not necessarily result in a smaller total harvest.

These two insights will help explain the modeled responses of fishers in Section 1.5. In general, stock and extraction risk effects remain the leading influences on guiding fishers input choices after buying insurance. Proposition 1.4.2 and Proposition 1.4.1 identify that within the complicated nexus of multiple input interactions, certain inputs may dominate the overall outcomes. Both propositions indicate that inputs that share risk effects (e.g. all inputs are risk increasing), ought to have the same conclusions as observed in Section 1.3. In fisheries with inputs with opposite risk effects, more information is needed to determine insurance effects on harvest. We turn to simulations in the following section to elucidate the ambiguity.

1.5 Numerical Simulations

Index insurance has asymmetric effects on harvest: contracts that reduce fishing effort do so modestly (median 2%), while those that increase it do so substantially (median 20%). We calibrate the model to estimates from Norwegian fisheries using three inputs from the parameters found in Asche *et al.* (2020). The inputs measured were fuel, f , capital, k , and labor, l . They used a non-linear estimator to calculate the production and risk parameters of a Just-Pope function across different fleets. Therefore, we assume the production function used by fishers is:

$$y(k, l, f) = k^{\alpha_k} l^{\alpha_l} f^{\alpha_f} (\hat{\beta} + \theta) + \omega k^{\beta_k} l^{\beta_l} k^{\beta_f} \quad (1.18)$$

Mean production, α , and risk effect, β , elasticities control the stock and extraction risk effects respectively. Each parameter is indexed to a particular input through the subscript, e.g. fuel mean production elasticity is α_f . Negative elasticities represent risk decreasing inputs while positive elasticities indicate risk increasing inputs. Table 1.1

shows the production and risk elasticities of the three fleets found in Norway. Asche *et al.* (2020) also estimates a fourth fleet, purse seiners. However the point estimate for mean production elasticity for labor was negative, and statistically not significant, which violates our assumption of increasing $f(x)$. Therefore, we exclude purse seiners from our analysis. Asche *et al.* (2020) aggregated by vessel type and not species, so there is no reasonable estimate for mean biomass, $\hat{\beta}$. They accounted for biomass using fixed effects in their regression, but without additional information we cannot parameterize the mean and variance of biomass. Therefore, our simulations normalize mean biomass to 1 and we assume the stock shocks, θ , have a normal distribution with $\theta \sim N(0, \sigma_\theta)$. We also assume extraction risk will follow a normal distribution with known variance $\omega \sim N(0, \sigma_\omega)$.

Table 1.1: Production and Risk elasticities of Norwegian Fisheries from Asche *et al.* (2020)

	α_k	α_l	α_f	β_k	β_l	β_f
Coastal Seiners	0.294	0.421	0.457	0.184	-0.432	0.119
Coastal Groundfish	0.463	0.421	0.355	0.965	-0.080	0.113
Groundfish Trawlers	0.210	0.106	0.531	-2.788	-0.110	-0.024

Fishers choose inputs and insurance coverage to maximize expected utility. We present their choice based on a ω contract, but we will run an equivalent model with a contract built on θ :

$$\begin{aligned}
 U &\equiv \max_{\gamma, k, l, f} \mathbb{E}[u] = \mathbb{E}[u(y(k, l, f) - c_k k^2 - c_l l^2 - c_f f^2 + \mathbb{I}(\gamma))] \\
 \mathbb{I}(\gamma) &= \begin{cases} -\rho\gamma & \text{if } \omega \geq \bar{\omega} \\ (1 - \rho)\gamma & \text{if } \omega < \bar{\omega} \end{cases} \quad (1.19)
 \end{aligned}$$

Equation 1.19 is solved through Monte Carlo simulation with 1000 random draws of stock and extraction risk⁵. We assume convex costs, for smoother convergence in the

⁵All simulations are conducted in R with accompanying code available at ngrimes@github.com/ibi-

maximization procedure. Constant Absolute Risk Aversion (CARA) utility is used so that utility remains defined if net profits are negative during the maximization procedure.

We compare the optimal choice of inputs with insurance versus without insurance by manually setting the insurance coverage to zero. Realized shocks are held constant between the two scenarios so that only the presence of insurance affects the choice of inputs. We report the percent the difference between input use and harvest to characterize the effects of insurance.

Parameters outside the production and risk elasticities will affect the magnitude of change, but not its direction ⁶. Because, Asche *et al.* (2020) do not estimate all model parameters, we vary the remaining parameters across a range of plausible values. Risk aversion will range from mild to extreme risk aversion, $\alpha \in \{1, 2, 3\}$, and shock variances take values $\sigma_\theta, \sigma_\omega \in \{0.1, 0.2, 0.3, 0.4\}$, yielding 192 parameter combinations per insurance contract specification. We summarize results using density plots and report the median change as an indicator the general change in input use and harvest.

Figure 1.1 shows the percent change in input use in each fishery with an insurance contract using ω as the index. Input changes generally align with the direction predicted by each input's own risk effect. For example, fuel and capital are risk increasing inputs for Coastal Seiners and saw small, but positive increases, while labor is risk-decreasing and declined. Overall changes are modest across all parameter combinations.

Every input in the Groundfish Trawler fleet is risk decreasing. With extraction risks contracts, fishers used less of every input. The largest decline was in capital, because capital possesses the strongest risk decreasing effect in the set of estimated fisheries.

The Coastal Seiners and Groundfish Trawlers indicate the conditions of Proposition 1.4.1 hold when risk effects are either clearly one direction, as in the Groundfish Trawlers,

behavior.

⁶See A.1.5 for simplified single-input simulation results illustrating this point.

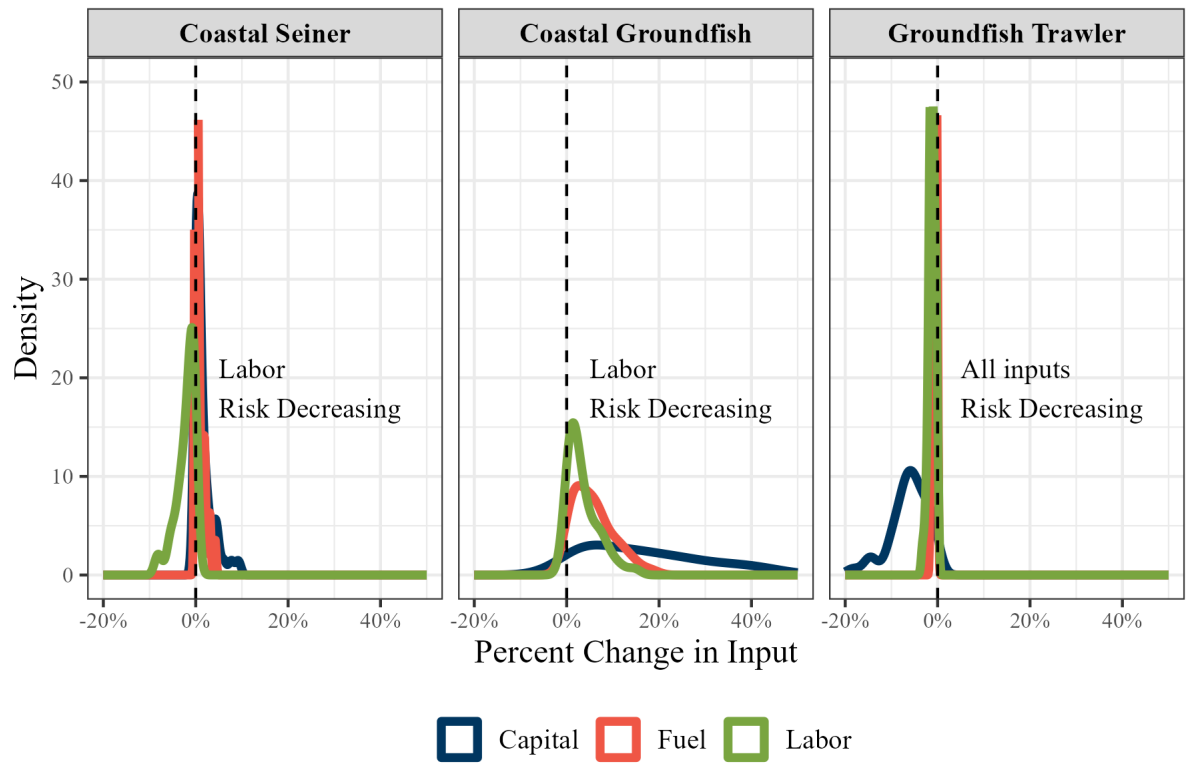


Figure 1.1: Density plots of the percent change in input use for each vessel type in Norwegian fisheries with contracts built on extraction risk ω . The dashed black line represents no change in input use. Risk decreasing inputs are labeled.

or roughly balanced across inputs, as in the Coastal Seiners. The Coastal Groundfish fleet illustrates what happens when this condition fails. Labor is risk-decreasing, yet consistently increased across simulations. Its risk-decreasing elasticity is small relative to the risk-increasing elasticities of capital and fuel. As insurance strongly incentivizes capital and fuel increases, complementarity in production requires labor to rise alongside them, overriding its direct risk effect.

Contracts designed on stock risk will always stimulate increased input use regardless of extraction risk effects (Figure 1.2). The one exception is capital in the Groundfish Trawler fleet, which still increases but at a substantially lower rate. Because capital is by far the most risk-decreasing input across all fleets, trawler fishers already rely on it heavily to manage risk. Insurance reduces some of that burden, but capital expansion is less necessary compared to the other fleets.

Changes in input use lead to changes in harvest. Figure 1.3 shows harvest changes in all fisheries with an insurance contract uses ω as the index. The Coastal Seiner fleet shows essentially no change in harvest with insurance. The Coastal Groundfish fleet increased median harvest by 10% with a maximum increase of 36%. Coastal Groundfish have the most risk increasing inputs out of the fisheries leading to the pronounced changes in harvest. Groundfish trawlers decreased harvest, primarily because insurance reduced capital use. Capital has low marginal productivity in this fleet, so an approximately 8% decline in capital use translates to only a median 2% reduction in harvest.

Applying an insurance contract indexed on θ instead of ω increases harvest in all fleets. (Figure 1.4). For instance, the percent change in harvest for Coastal Seiners is indistinguishable from zero. With a θ index contract, Coastal Seiners would increase harvest by 18% (Figure 1.4). Even in the Groundfish Trawler fleet, where risk-decreasing capital dominates, fishers expand production when insurance shields them from biological risk. This contrast between contract types most directly illustrates the potential for

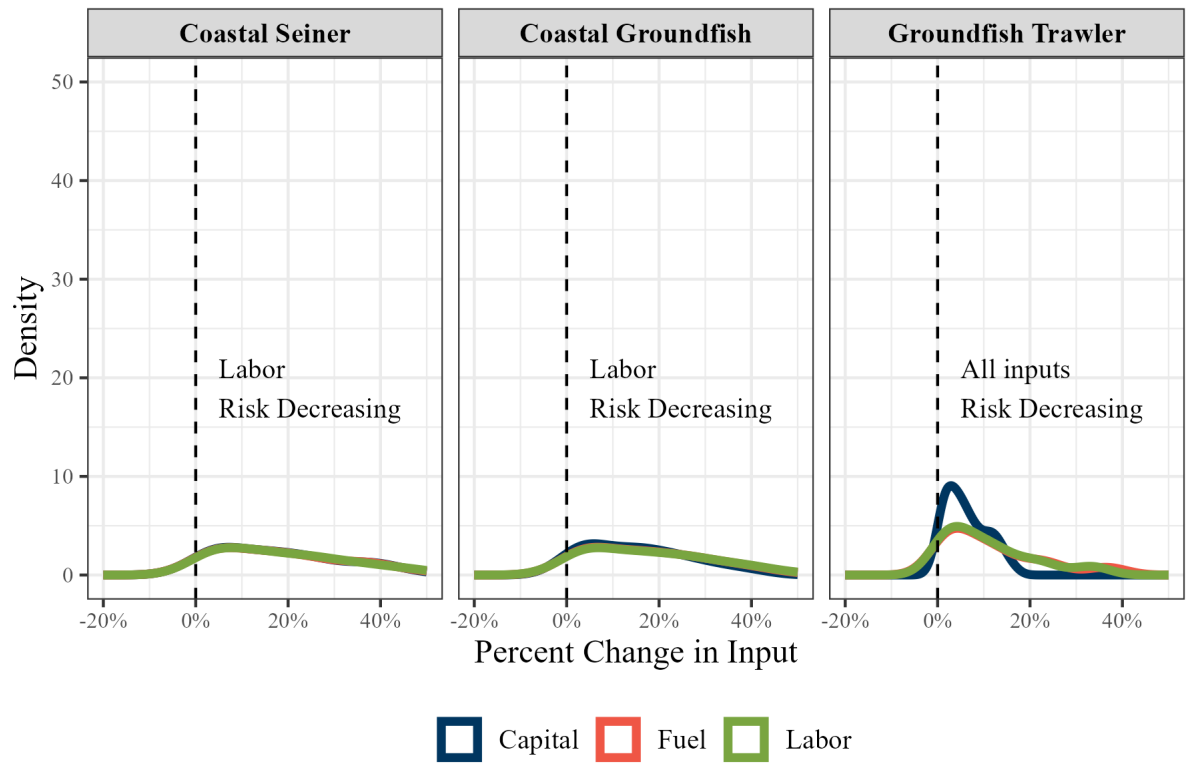


Figure 1.2: Density plots of the percent change in input use for each vessel type in Norwegian fisheries from an insurance contract triggered on extraction risks θ . The dashed line represents no change in harvest. Risk decreasing inputs are labeled.

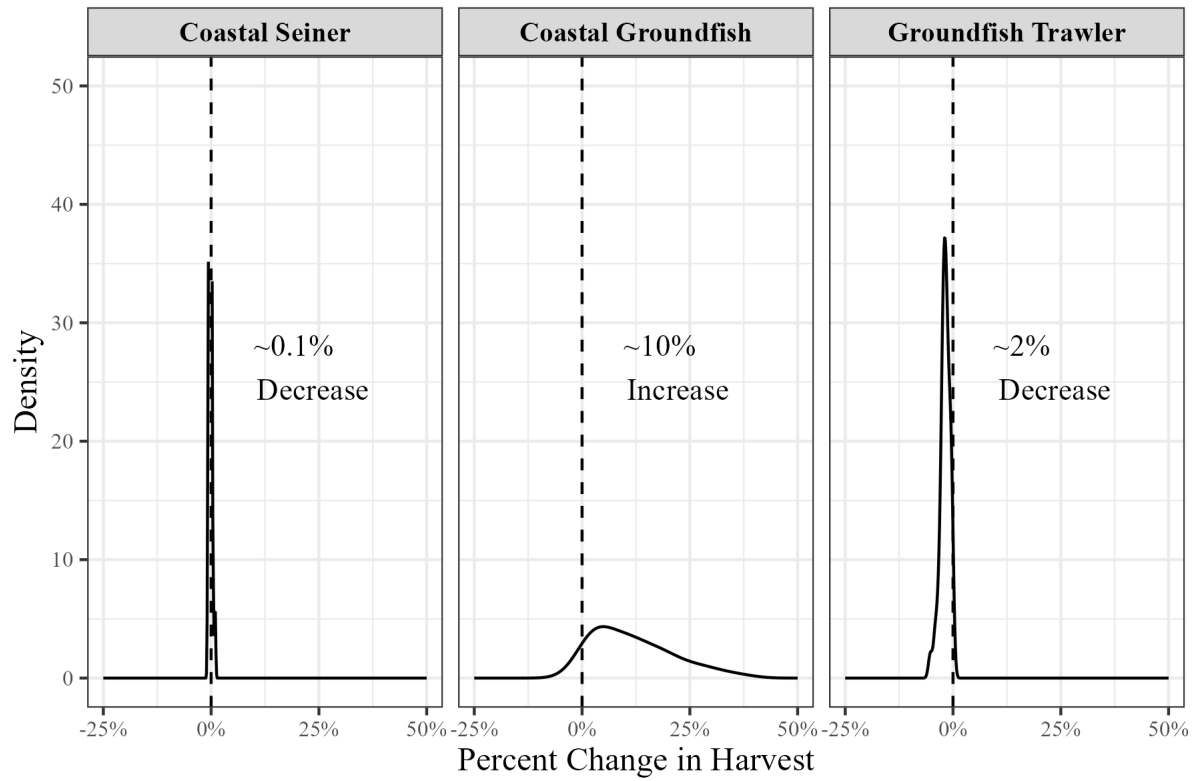


Figure 1.3: Density plots of the percent change in harvest for each vessel type in Norwegian fisheries from an insurance contract triggered on extraction risks ω . The dashed line represents no change in harvest. The text labels represent the median percent change in harvest for each vessel type.

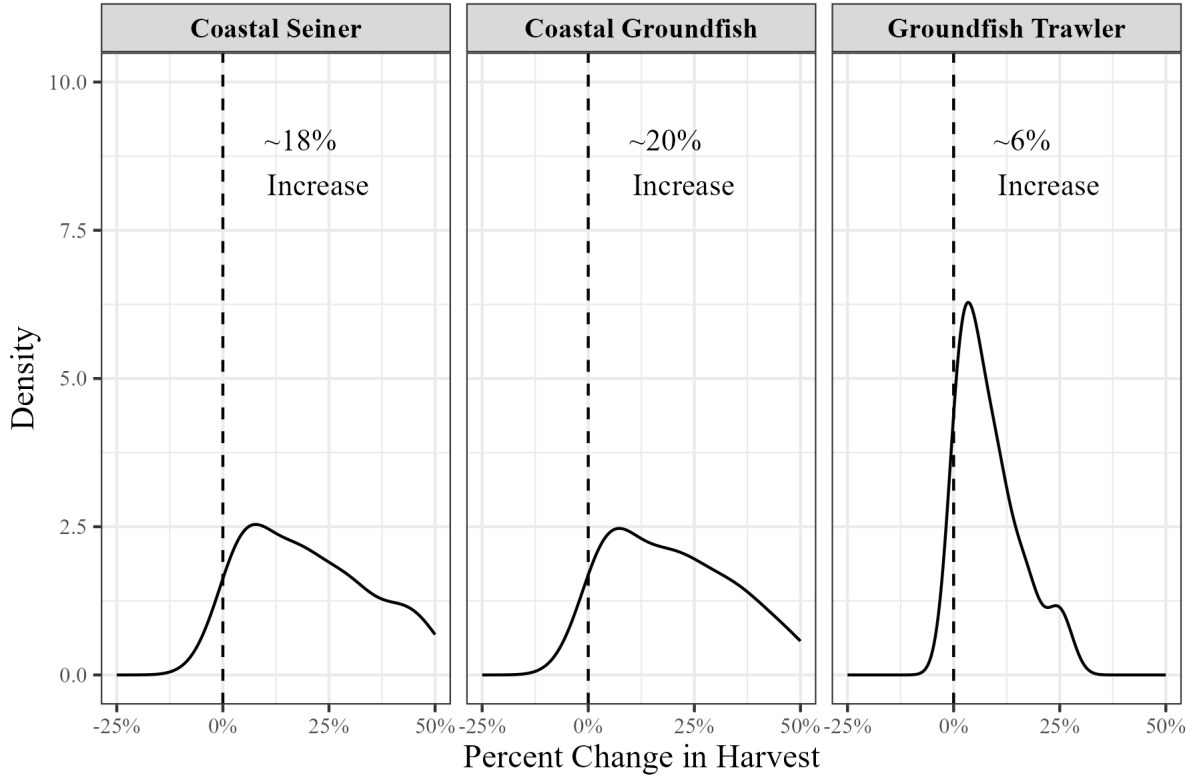


Figure 1.4: Density plots of the percent change in harvest for each vessel type in Norwegian fisheries with insurance contract indemnified on biological risk θ . The dashed line represents no change in harvest. The text labels represent the median percent change in harvest for each vessel type.

index insurance to induce harvest increases that would not occur under extraction-risk contracts, and underscores the importance of contract design when insurance is introduced alongside harvest constraints.

1.6 Discussion

Index insurance will change fisher behavior, driven by risk effects and contract design. The incentive pathway toward increased harvest is substantially stronger than toward decreased harvest and must be accounted for before implementation to prevent long-term stock degradation that would undermine fishers' welfare. Three approaches can guide

sustainable behavior change: identifying fisheries with risk-decreasing inputs, designing contracts against extraction risk, and working with management to impose sufficient constraints.

Fishery input risk effects dictate the direction of harvest change, but ex-ante identification of input risk effects in fisheries is challenging. Extraction risk effects remain an elusive concept in fisheries, and need to be estimated in order to predict more accurate behavior changes of fishery index insurance. Crop covers and pesticide provide clear examples of risk decreasing inputs in agriculture, but what do risk decreasing inputs look like in fisheries? Labor is perhaps the more intuitive risk decreasing input. Technical expertise of crew and captains can hedge against luck when fishing (Alvarez *et al.*, 2006). Better trained crew can deploy gear in a safe and timely manner, increasing the likelihood of effective sets.

Fuel as a risk increasing input in fisheries makes intuitive sense as well. Fuel is used to power vessels and is a direct cost of fishing. Fishers explore productive fishing grounds for the best location. Every hour at sea increases the harvest reward, but also the chances of failure.

Capital is a more complex input, because it is shown to be both risk increasing and decreasing. Capital in fisheries typically refer to vessel tonnage, engine power, and gear technology. Asche *et al.* (2020) noted that the trawler fishery, $\beta_k = -2.7$, was primarily an ocean going fleet that could move to the fish and handle adverse weather more readily. The authors postulated the flexibility to pursue fish reduced overall production variance. Quota allocations in the coastal fisheries are determined by vessel size with smaller vessels receiving proportionally more quota. Increasing vessel size would increase risk by introducing more variable quotas. The context of the fishery likely determines the risk effects of capital.

Specifying contracts on stock risk or extraction risk has clear differences. However, the

leading candidates for possible indices in fisheries index insurance are currently weather variables most often associated with biological stock risks (Watson *et al.*, 2023). Designing contracts solely on these variables may lead to harvest increases that run contrary to conservation goals.

The structural limitations imposed by assumptions on stock risk may drive this result. Most bioeconomic models simplify the complex effects of stock dynamics into multiplicative or additive forms as modeled in this paper. Instead, different forms of risk could be embedded into the biological component of fishery models. Stock variance could be greater in overfished stocks instead of healthier ones, reflecting more vulnerability in weaker states (Sims *et al.*, 2018). Adapting alternative, more biologically focused specifications of stock risk could change the behavioral effects of insurance. Fishers may be more willing to expose themselves to greater risk at more vulnerable stock levels with insurance. Alternatively, insurance could help mitigate risk and incentivize fishers to move toward healthier stocks with less variance by alleviating income pressures to fish. Further analysis is required to understand the full implications of stock risk effects in fisheries.

Management may also limit stock risk, and interact with insurance in complex ways. Our analysis explicitly modeled scenarios without the existence of management. We wanted to analyze the interaction of insurance on fisher behavior in unconstrained settings first to derive a clearer incentive structure. Managers would still need to understand the underlying incentives of index insurance to ensure effective binding constraints. Most fisheries are managed in some form. The interaction between management and insurance may be complementary or substitutes. For example, well managed fisheries that have responsive harvest control rules may not need insurance. Stock risk could be reduced so that only contracts on extraction risks would be viable. Insurance demand and uptake may be low in these fisheries.

Insurance could instead complement management to provide the financial relief that management cannot offer. Managers often focus on the biological health of the fishery that can run at odds with fishers' desires to enhance their income. Insurance can act as the financial relief to allow managers to pursue more active strategies to protect fish stocks without political resistance from lowered quotas. Additionally, management can provide the constraints on insurance moral hazard so the income smoothing benefits are passed to fishers, but not the long term degradation. The interaction between insurance and management requires further investigation especially with the numerous management strategies that exist in fisheries.

The transfer between inputs and insurance reflects the substitution between self-insurance and formal insurance (Quaas and Baumgärtner, 2008). If index insurance is designed to reduce fishing capacity, efforts must be made to ensure that it does not take away from the self insurance capacity of fishers. Labor appears to be consistently risk reducing and acts as a form of self insurance. If index insurance incentivizes captains to hire less crew, the stock of fish may be preserved, but less employment may reverberate throughout the community. Fishing is often a primary employment opportunity in coastal communities. The resiliency of the community would be compromised rather than enhanced with fewer jobs. Contract stipulations could mandate that only cost expenses are covered by payouts thereby including lost wages to the crew. Agriculture contracts often are designed to directly cover expenses (He *et al.*, 2020).

Our model only directly models behavior change through moral hazards. Index insurance could be designed to incentivize other forms of sustainable behavior change. We define three pathways insurance can change behavior: Moral hazards, Quid Pro Quo, and Collective Action. Moral hazards were proven in this paper to have ambiguous impacts controlled by the risk characteristics of fishery inputs. The incentives of moral hazards will always exist, therefore other measures could be taken to either limit the downside

behavioral effects of insurance or stimulate other forms of sustainable behavior.

Quid Pro Quo expands contract design to explicitly build in conservation measures. Fishers would be required to adopt sustainable practices in order to qualify for insurance. Quid Pro Quo is already used in agricultural insurance in the form of Good Farm Practices. Farmers must submit management plans to US Risk Management Agency that clearly outline their conservation practices in order to qualify for insurance. Working closely with management agencies, insurance companies could design contracts that require fishers to follow fishery specific management practices. For example, fishers may be incentivized to use more sustainable gear types, have an observer onboard, or reduce bycatch. A stipulation in the COAST program is fishers must register their vessels with the participating countries fisheries department (Sainsbury *et al.*, 2019). This requirement has brought greater data clarity to small scale Caribbean fisheries.

Further research would need to uncover the full impact of Quid Pro Quo, but an initial hypothesis would be fishers will be willing to adopt sustainable practices so long as the marginal gain in utility from the insurance is greater or equal to the marginal costs of the stipulated sustainable changes. Otherwise fishers will not want to buy the contracts, and the insurance has no binding constraints to change the fishery.

Collective action ties insurance premiums to biological outcomes to leverage the political economy of the fishery. Insures could reduce premiums in fisheries that have robust management practices such as adaptive harvest control rules, stock assessments, or marine protected areas in the vicinity. Fishers could either pressure regulators to adopt these actions or form industry groups to undertake the required actions. Insurers would agree to this if triggers are connected to biological health so that negative shocks are less frequent and thus payouts occur less. Fishers gain from the reduced insurance premium and the increased sustainability of harvest with rigorous management in place.

Ultimately, if index insurance is to be used in fisheries, it must be designed with clear

objectives and intentions. Index insurance can meet objectives of income stability and risk reduction, but there has been an implicit assumption by practitioners that index insurance will always lead to improved sustainability. Our results directly contradict that claim with the use of traditional models. Without considering the behavior change of fishers when adopting insurance, the outcomes may not be as expected. New insights derived from this paper will help guide the efficient and sustainable implementation of fisheries index insurance.

Chapter 2

Finding Suitable Indices for Novel Fisheries Index Insurance Program

2.1 Introduction

Fishers face enormous environmental variability that impacts their livelihoods. Extreme weather events that degrade stock health such as stagnant upwelling or marine heatwaves can lead to significant losses in fishery productivity (Smith *et al.*, 2023; Szuwalski *et al.*, 2023; Villaseñor-Derbez *et al.*, 2024). These shocks can devastate fishing communities, leading to income loss and food insecurity (Holland and Leonard, 2020; Jardine *et al.*, 2020). The need for financial tools to protect fishers from these shocks has never been greater (Mumford *et al.*, 2009; Sethi, 2010; Kasperski and Holland, 2013; Sumaila *et al.*, 2021). Index insurance has emerged as a potential financial policy to protect fishing communities during such disasters, but accurately identifying suitable indices for fisheries has impeded widespread deployment (Watson *et al.*, 2023; Hobday *et al.*, 2025). This paper is the first to empirically construct index insurance contracts to protect against fluctuations in fishery biological productivity.

Index insurance pays fishers when an independently verified environmental index, such as sea surface temperature, crosses a preset threshold called the trigger. The index is ideally chosen to be highly correlated with harvest, and the trigger represents a critical value beyond which harvest is expected to fall below historical averages. For example, salmon have strict thermal tolerances (Eliason *et al.*, 2011; Mayer *et al.*, 2024). An insurance contract could be designed to compensate fishers when water temperatures exceeds thresholds that stress salmon leading to less harvest.

Using an independent index enables faster payouts, eliminates claim verification, reduces costs, and limits moral hazard compared to traditional indemnity insurance (Barnett and Mahul, 2007). Moral hazards are changes in fisher behavior in response to owning insurance. In an indemnity insurance program, fishers may choose to purposely reduce harvest as distinguishing intentional underperformance from genuine environmental loss is nearly impossible (Herrmann *et al.*, 2004; Watson *et al.*, 2023). Index insurance eliminates "fishing the insurance", which is favorable to insurance companies, but may still incentivize fishers to change harvest decisions (Grimes *et al.*, 2026).

The COAST program is the only extant index insurance product for fisheries (Sainsbury *et al.*, 2019). It is a pilot program that insures small island nations in the Caribbean from hurricanes. It uses indices of wave height, wind speed, and storm surge to initiate payouts once they fall below the trigger. There is growing interest to expand index insurance to cover other environmental shocks, including biological productivity shocks. However, significant market barriers have limited widespread implementation (Watson *et al.*, 2023; Hobday *et al.*, 2025).

The primary market barrier is empirically constructing contracts that sufficiently reduce basis risk. Basis risk is the potential for a policyholder's actual loss to not align with the contract payouts. For example, if a fisher suffers poor catch, but the index does not exceed the trigger, then the fisher will not receive payouts. The opposite may occur

where insurance companies payout despite fishers receiving high catch. Basis risk lowers demand for index insurance and leads to exorbitant premium rates (Binswanger-Mkhize, 2012; Clarke, 2016; Clement *et al.*, 2018).

Identifying triggers and indices that are highly correlated to loss is the best way to eliminate basis risk (Jensen *et al.*, 2019). Agricultural index insurance has refined techniques to build and price contracts over the last 20 years (Jensen *et al.*, 2016). The most common design strategy is to match individual farms to the nearest meteorological stations, then use simple linear regression to model yield-index distributions (Miranda and Farrin, 2012; Spicka and Hnilica, 2013; Conradt *et al.*, 2015; Dalhaus *et al.*, 2018; Benso *et al.*, 2023; Mapfumo *et al.*, 2017). Premiums are then calculated based on the payout distribution of prior years for a given contract.

However, fisheries face more difficult data and empirical challenges than agriculture. Predicting fishery output from environmental variables is notoriously difficult. It is widely established that climate and weather affect fish populations (Lehodey *et al.*, 2006), but even the most advanced fishery stock assessment models use little to no environmental data for projections (Privitera-Johnson and Punt, 2020). Spatial distributions of fisheries can cover large areas making it unclear where and how much specific variables impact biological abundance. Additionally, if environment to catch relationships can be established, they are often nonlinear and interact with multiple variables. A feature unique to fisheries is that the biological dynamics of fish reproduction can generate persistent low-catch states in the aftermath of a large negative shock (Hilborn *et al.*, 2003).

Fishery management is also a unique challenge to navigate empirically that is absent from agriculture insurance. Good fisheries management provides the necessary data to model environment to catch dependency, but can also sever the connection. For example, many fisheries in the United States transitioned from open access to individual transferable quota systems in the early 2000s (Costello *et al.*, 2008; Free *et al.*, 2025).

Distortions in catch would be attributable to shifts in management regimes rather than weather (Färe *et al.*, 2015). In the years following the implementation of quota systems, catch levels became primarily influenced by management choices rather than environmental conditions.

Despite these challenges, innovations in fishery and oceanographic data collection, and increased exposure of fishers to environmental variability, suggest a new opportunity has arisen to reconsider the use of index insurance in fisheries. New methods including machine learning algorithms could better capture the complex, nonlinear relationships between environment and fishery productivity.

This paper is the first to empirically evaluate the feasibility of index insurance for fisheries using univariate, first-order linear methods established through application in agriculture, and novel machine learning techniques to address the complexity of fishery data. I use the Market Squid Fishery (*Doryteuthis opalescens*) in California as a case study to test insurance contracts built on five different prediction models with twelve environmental and biological variables. Machine learning algorithms capture the multivariate and non-linear dimensions of catch and potential indices. I evaluate whether the contracts improve fisher welfare by determining how much better off fishers would have been if index insurance was available in the last decade. I assess whether insurance companies could feasibly offer contracts within a private market to remain solvent by examining the upper limit a fisher would be willing to pay for a given insurance contract.

Fishers are more willing to pay for insurance contracts that more accurately estimate the catch to environmental relationship. Only one index, krill abundance, in univariate first-order linear models improved fisher welfare at the market price. When charging a competitive market premium, the contracts built with random forest, regularized random forest, and support vector machine algorithms were profitable for insurance companies.

Machine learning algorithms create "black-boxes" that may lower fishers' trust in

relying on complex algorithms as the basis of their payout schedules. I use permutation variable importance metrics to isolate the primary variables influencing model predictions. The leading variable of influence in the nonlinear models included upwelling measures, regional El Niño metrics, and krill abundance. Communicating to fishers the relative influence of each variable is crucial to build trust and transparency. Overall, there is potential for index insurance to be feasible in a private market, and provide fishers with protection against environmental variability.

These results contribute to three literatures. Fisheries risk management includes formal and informal means of mitigating risk. However, developing formal financial tools to manage fisheries risk has been limited. Prior studies have explored the theoretical application of insurance in fisheries (Herrmann *et al.*, 2004; Mumford *et al.*, 2009; Sethi, 2010; Watson *et al.*, 2023; Hobday *et al.*, 2025), but few have empirically tested the feasibility of such programs. Hobday *et al.* (2025) provides a compelling case for index insurance in fisheries as well as a comprehensive review of the potential barriers. My study addresses a key limitation highlighted in Hobday *et al.* (2025) while expanding the evaluation of a new formal risk mitigation tools that could be used by fishers to manage environmental risk.

Within the index insurance literature, there has been a growing application of machine learning to improve index design (Feng *et al.*, 2019; Cesarini *et al.*, 2021). Payout schedules limited to linear payouts introduce unnecessary basis risk that can be mitigated with neural networks directly predicting the triggers (Chen *et al.*, 2024). Machine learning models can also improve the estimation of crop yields (van Klompenburg *et al.*, 2020). Improved estimation of crop yields leads to better insurance performance (Schmidt *et al.*, 2022). My study further demonstrates the value of machine learning for index design, but reinforces the challenge of communicating complex models to policyholders and additional considerations that influence pricing.

The application of machine learning is growing in fisheries. Neural networks can improve management strategy evaluation by allowing greater exploration of more state variables in the choice of harvest control rules (Montealegre-Mora *et al.*, 2025). Neural networks are also capable of predicting fishing activity in the global fleet using GPS data from vessels (De Souza *et al.*, 2016). Ensemble models built through combinations of random forests, boosted trees, and dynamic linear models improve Bristol Bay sockeye salmon forecasts by 15% compared to a standard lagged regression model (Ovando *et al.*, 2022). Important environmental variables to groundfish populations were uncovered using single index varying coefficient models regularized with LASSO (Correia, 2021). Random forests models better predict catch in Indonesia than traditional linear models (Rahman *et al.*, 2022). Random Forests models have also been used to predict fishery catch in the California Market Squid Fishery to isolate important biological and ecological variables (Allen Akselrud, 2024). My study builds on this literature by demonstrating the value of machine learning for predicting fishery productivity through environmental covariates, even in small data sets.

The rest of the paper is structured as follows. Section 2.2 describes the design of index insurance contracts used in this study as well as demonstrating how imperfect prediction models lead to basis risk. Section 2.3 describes the algorithms used to predict fishery productivity, and how variables of importance were identified. Section 2.4 describes the characteristics of the market squid fishery that make it suitable for index insurance. Section 2.5 includes the data collection, transformations, and sources. Fisheries data comes from newly open-access sources provided by the California Department of Fish and Wildlife. Environmental variables are collected from a variety of sources to explore a wide range of potential indices. Section 2.6 presents the primary findings of the paper including the performance of all models. Future steps and considerations for broader implementation of fishery index insurance are outlined in Section 2.7.

2.2 Insurance Framework

Index insurance is designed to protect policyholders from suffering losses below critical yield thresholds called triggers. The trigger, y^* can be arbitrarily chosen by the insurer, but ought to accurately reflect a state of loss for fishers. For example, y^* could be set at 10% of maximum sustainable yield. Actuaries then define an index estimated from the expected harvest conditional on weather variables. If that index falls below the trigger insurance will compensate fishers through an indemnity payment $I(w)$:

$$I(w) = \max(y^* - \mathbb{E}[y|w], 0) \quad (2.1)$$

A common trigger in agriculture is average yield, $y^* = \mathbb{E}[y]$. Any index values below average would initiate a payout. The index, $\mathbb{E}[y|w]$ captures the weather to yield relationship. The trigger and index can be translated into direct measurements of weather through an inverse function $h^{-1}(\mathbb{E}[y^*|w])$. However, the translation can be difficult to interpret for multivariate models. Therefore, I leave the predicted harvest as the index, which can be modeled through an estimator $g(\tilde{w})$:

$$\mathbb{E}[y|w] = g(\tilde{w}) + \tilde{\eta} + \tilde{\epsilon} \quad (2.2)$$

Formally, basis risk is the combined stochastic effects of $\tilde{\eta}$ and $\tilde{\epsilon}$. The model error, $\tilde{\eta}$, arises from the inability to perfectly estimate the environment to yield relationship. The idiosyncratic error, $\tilde{\epsilon}$, arises from all other shocks to yield that are not related to the environmental shock. This term captures the effects of management, input choices, differences in individual vessels, and all other environmental variables outside of w . Well designed contracts minimize the negative effects of design risk stemming from η . For example, a perfectly estimated environment to harvest relationship would minimize η to

zero.

The estimation of $g(\tilde{w})$ is extremely difficult in fisheries. However, the estimation does not need to be perfect or even statistically significant to provide value to fishers. The model only needs to capture enough of the environment to harvest relationship to provide sufficient protection with the insurance contract.

Structural forms of all models are presented in detail in Section 2.3. For now, the general model output will be represented as $\hat{y}(w)$ stemming from estimator $g(\tilde{w})$, where $\hat{y}(w)$ is the predicted harvest from observed weather variables.

I set the trigger to $y^* = c\mathbb{E}[y]$, where c represents the coverage level and replace the index with the predicted value of harvest.

$$I(w) = \max(c * \mathbb{E}[y] - \hat{y}(w), 0) \quad (2.3)$$

Equation 2.3 indicates fishers will receive the difference between the long run average of catch and the model predicted outcome from observed weather variables. The coverage level, c , represents the level of protection offered by the contract. The main results of the paper set coverage to 100%, where any predicted catch below long run average triggers a payout. In the online supplementary information, multiple coverage levels are tested at stricter levels.

Premiums are calculated by determining the expected payout of the contract times a premium loading factor, m :

$$\rho(w) = \mathbb{E}[I(w)]m \quad (2.4)$$

I use burn rate analysis to calculate the expected payout in Equation 2.4. Burn rate analysis uses past realizations of environmental variables to create a distribution of payouts that would have been observed if the policy was active over that time. The mean

of the payout distribution is used as the statistic for $\mathbb{E}[I(w)]$. Burn rate analysis is a common method used by actuaries to price index insurance contracts, and is suitable in this setting because of the short time period of analysis (Jewson *et al.*, 2005).

2.2.1 Utility evaluation

Evaluating the performance of index insurance contracts through a utility framework provides more accurate assessment of the impact basis risk has on fishers willingness to pay for insurance (Conradt *et al.*, 2015; Kenduiywo *et al.*, 2021). Utility is an economic measure that captures an individuals tolerance for risk. Extremely risk averse policyholders will avoid index insurance all together with any level of basis risk as the downside risk of not receiving payouts when necessary outweighs the benefits of having insurance (Clarke, 2016). Therefore, assessing contracts based on utility will provide more information on fisher welfare especially in extreme events than simply comparing the incidence of incorrect payout schedules.

I calculate expected utility with, u_i , and without insurance, u_{ni} , in the test set using isoelastic utility in Equation 2.5:

$$\begin{aligned} u_i &= \frac{1}{n_{test}} \sum_t^{n_{test}} \frac{(y_t + I_t(w_t) - \rho_t)^{1-\eta} - 1}{1 - \eta} \\ u_{ni} &= \frac{1}{n_{test}} \sum_t^{n_{test}} \frac{y_t^{1-\eta} - 1}{1 - \eta} \end{aligned} \tag{2.5}$$

Where y_t is the observed harvest per fisher in year t , $I_t(w_t)$ is the payout from the insurance contract based on weather variables w_t , and ρ_t is the premium paid for insurance. The number of years in the test set determines n_{test} . The risk aversion term η is set to 1.5 in the main results to represent moderate risk aversion, but adjusted in the supplementary information to explore mild ($\eta = 0.5$) and large ($\eta = 3$) risk aversion. Fishers

have a wide range of idiosyncratic risk preferences (Brick *et al.*, 2012; Eggert and Martinsson, 2004), each of the modeled levels correspond to observed risk aversion in fishers. Isoelastic utility is a form of constant relative risk aversion (CRRA) where it is assumed fishers maintain a constant proportion of risk preference across all levels of wealth. Given the large fluctuations in income observed in the data, CRRA risk preferences allow more consistent comparison of utility across large shocks. The expected utility with insurance, u_i , includes the payouts from the insurance contract minus the premiums paid. The expected utility without insurance, u_{ni} , is the utility solely from catch.

I determine whether fishers are better off with insurance by calculating the percent change in utility from having insurance in Equation 2.6:

$$u_{rr} = \frac{u_i - u_{ni}}{u_{ni}} \quad (2.6)$$

Positive values of u_{rr} indicate fishers are better off with insurance, whereas negative values indicate fishers are worse off with insurance.

I measure the profitability of the insurance contract as the willingness of insurance companies to provide a contract. Insurance companies use a wide variety of pricing methods such as Value at Risk (VaR) where the tails of the distribution of payouts receive greater emphasis (Mapfumo *et al.*, 2017). The premium loading factor is then adjusted to prevent downside risk for the insurance company. The premium loading factor is the multiple of the expected payout that insurance companies charge to cover administrative costs and earn profit. However, without information on the risk tolerance of insurance companies or their elasticity to supply insurance, I identify the bounds of a market by adjusting the premium and compare whether fishers would be willing to pay for contracts where insurance companies earn a profit.

I calculate the premium loading factor in Equation 2.4 that makes fishers indifferent

between having insurance and not having insurance where $u_{rr} = 0$ as m^* . Varying m only affects the premiums paid. The payout schedule is solely determined empirically by the models. Values of m^* greater than 1 indicate fishers are willing to pay more than the expected payout for insurance, whereas values below 1 indicate subsidies will be needed to stimulate demand.

m^* will be called the “market” premium as it represents the upper bound an insurance company could charge for insurance. I calculate the loss ratio, $lr = \sum I(\omega) / \sum \rho$, at both actuarially fair and market premiums to analyze the market viability of a contract. Loss ratios above 1 indicate insurance companies lost money on the contract, whereas loss ratios below 1 indicate insurance companies are profitable. If a contract at m^* leads to $lr < 1$, then the contract is viable in a free market. Insurers can use any m less than the market m^* and still encourage fishers to purchase insurance.

2.3 Methods

I use five models to predict yearly catch $\hat{y}(w)$ that serves as the index within Equation 2.3. Simple linear models are the base model given its ubiquitous use in index insurance policies. Simple linear models create first-order single index contracts that use only one environmental variable. I refer to all simple linear regression models as “univariate” to differentiate between the multivariate models. The four multivariate models predictor models will be LASSO regression, random forest, regularized random forest, and support vector machine.

I use a rolling window cross validation method to assess the out of sample predictive quality of each model, evaluate utility with insurance in the test set, and tune hyperparameters of the multivariate models (Ovando *et al.*, 2022; Allen Akselrud, 2024). The data is split into an initial training window from 1990-2013 to provide enough data to

accurately calibrate each model. From the trained model, a single prediction is made with environmental data from the next year. Whether the contract pays out according to Equation 2.3 is recorded. The premium for that year is calculated using burn rate pricing on the training set. In the next period, the training window rolls forward one year to include 1990-2014. The model is retrained and a prediction is made for 2015. This procedure continues until the end of the data set in 2023. Expected utility, Equation 2.5 is calculated for the entire test set based on the payout schedule and premiums from the predictor models.

The rolling window validation strategy is well suited for time series data where temporal autocorrelation may be present. I do not provide a validation window for parameter tuning as the time series is short. Withholding observations may lead to more overfitting whereas I can use the test set to tune hyperparameters. Additionally, the rolling window mimics policywriters' strategies where they update their actuarial models each year to provide the most accurate pricing information.

Root mean squared error (RMSE) will serve as the metric to evaluate out of sample predictive performance of each model in the hyperparameter tuning.

2.3.1 Univariate Models

Regression coefficients with perfect correlation replicate the optimal choice of scale in index insurance contracts (Mahul, 1999). Combined with the ease of implementation, first-order linear models on single weather indices are the most common design choice for index insurance policies (Benso *et al.*, 2023).

Annual catch is regressed on each environmental variable individually using Ordinary Least Squares (OLS):

$$y_t = \beta_0 + \beta w_t + \epsilon_t \quad (2.7)$$

Linear models are preferred in index insurance because they provide a simple, transparent relationship between the environmental variable and catch. For example, it is possible to show the output of a contract built on linear regression in terms of the environmental variable directly:

$$I(w) = \max(\beta_1 c * (\frac{\mathbb{E}[y] - \beta_0}{\beta_1}) - w, 0) \quad (2.8)$$

The trigger, $(\frac{\mathbb{E}[y] - \beta_0}{\beta_1})$ is now expressed directly in units of the index while still interpreted as a yield threshold. This structure allows for clear communication to fishers about payouts. For example, if sea surface temperature is the index, then the trigger can be expressed as $12^\circ C$. Any realized temperature, w , below $12^\circ C$ would initiate a payout.

2.3.2 LASSO Regression

Least Absolute Shrinkage and Selection Operator (LASSO) regression is a popular regularization technique to assist model selection. It attempts to minimize the residual sum of squared errors through OLS, but adds a penalty constraint on the absolute sum of selected coefficient values (Equation 2.9).

$$\hat{\beta}^{lasso} = \arg \min_{\beta} \left\{ \sum_{i=1}^n (y_i - \beta_0 - \sum_{j=1}^p w_{ij} \beta_j)^2 + \lambda \sum_{j=1}^p |\beta_j| \right\} \quad (2.9)$$

Where, y_i is catch, β the regression coefficients, n , the number of observations, p the number of environmental variables, and w the total collection of environmental variables. The λ is the penalty term that controls the amount of shrinkage. Models are trained using the `glmnet` package in R (Friedman *et al.*, 2010). The λ that minimizes RMSE is

selected through a grid search method. This choice is to ensure the most parsimonious model that still captures the most important weather variables. Reducing the number of variables used to define a trigger payout will simplify the contract substantially.

2.3.3 Random Forests

Random forests are tree-based ensemble models that capture non-linear interactions through recursive partitioning. Each tree is built on a bootstrapped sample of the training data. At each split, a random subset of predictor variables is chosen to determine the best split. The final prediction is the average of all the trees in the forest. Random forests have been shown to outperform traditional regression models in fisheries applications (Ovando *et al.*, 2022; Rahman *et al.*, 2022; Allen Akselrud, 2024).

The high dimensionality of the data and few observations will make random forests susceptible to overfitting. I address this high feature low observation problem through feature selection and regularized random forests. Certain environmental variables are likely to be highly correlated with each other. I select the indices with the highest correlation to catch for five categories of variables: Temperature, regional indices, upwelling, prey, and paralarvae abundance.

Regularized random forest provides an agnostic, data driven methodology for feature selection. Regularized random forest computes permutation importance scores for each variable during out of bag testing (Deng and Runger, 2013). If the increase in overall performance for a given variable is lower than a specific threshold, it is removed from the model. Similar to LASSO, it allows for an unbiased assessment of important variables. I can compare whether my feature selection on expertise is accurate by examining the variables selected by the regularized random forest.

I tune three parameters to optimize the random forest model. The number of variables

randomly sampled at each split, *mtry*, the minimum number of observations in a terminal node, *nodesize*, and the maximum depth of each tree. I manually construct a parameter grid to search for the combination of parameters that minimize RMSE in the test set. Max depth is set to small values, while *nodesize* has higher than default thresholds to reduce overfitting bias. The small number of observations in the data set ($n = 34$ years) necessitates more conservative parameter choices. Models are built using the **ranger** package in R (Wright and Ziegler, 2017).

Regularized random forest requires one additional tuning parameter along with the three used in standard random forests. The regularization parameter, γ_{rrf} , controls the threshold a variable will be added contingent on the permutation score. It is normalized from 0-1 with 1 acting as the most aggressive regularization. Models are built with **RRF** package in R (Deng and Runger, 2013).

2.3.4 Support Vector Machine

Support vector machine (SVM) constructs vectors that define an error insensitive margin when used for regression. The algorithm then minimizes a loss function on the slack points outside the support vectors. I use a radial basis function kernel to map the predictors into a higher-dimensional feature space, enabling the algorithm to capture nonlinear patterns without explicitly defining transformations of the input variables. Support Vector Machines work well in time series data with low observations and high dimensionality (Sapankevych and Sankar, 2009).

Model complexity is controlled by the regularization parameter, C , which controls the width of the support vectors. A smaller C allows for a wider margin, placing more data points within the support vectors and enhances generalization. A larger C aims to minimize the error in each training point correctly, which may lead to overfitting. The

kernel coefficient, γ_{svm} , defines the influence of individual training examples. A small γ_{svm} implies a broader influence, leading to less sensitivity to outliers, while a large γ_{svm} focuses on nearby points, capturing more intricate patterns but risks overfitting. I use a grid search method to tune C and γ_{svm} to minimize RMSE in the test set. Models are built using the `kernlab` package in R (Karatzoglou *et al.*, 2004)

2.3.5 Variables of Importance

Machine learning algorithms are inherently “black boxes” that sacrifice interpretability for predictive accuracy. Fishers will be less likely to purchase complicated products that do not correspond to their experiences (Patt *et al.*, 2009). Extracting the relative contribution of weather variables will assist translating products to fishers. Additionally, it can help ground-truth the chosen variables with previous biological modeling.

I extract importance measures using permutation for all the multivariate models. Permutation randomly modifies a variable’s value then calculates the change in the model performance. As models are updated in each period, I will have n_{test} models each with their own permutation scores. I examine the importance of each variable in a model over the rolling training window.

2.4 Market Squid Fishery

The California Market Squid Fishery is an ideal candidate to assess the viability of index insurance due to its high economic value, simple management system, excellent data, and “corn-like” biological attributes.

Market squid is the second most valuable in California with an average annual ex-vessel value of \$48 million since 2013. By landing weight, it is the largest fishery in California with total catch exceeding half a million tons since 2013. Fishing predominately

occurs in the Santa Barbara Channel during October and November. It is vulnerable to large fluctuations in catch, which threatens livelihoods during disastrous years. Index insurance would offer much needed stabilization to fishers in this volatile fishery.

The fishery has been consistently managed since 2005 with a permit entry system and a maximum annual catch limit of 118,000 metric tons. Prior to 2005, the fishery was open access with fishers only paying for a license and a landing tax. The number of licensed fishers dramatically declined in the implementation of the permit system in 2005. I adjust for the change in permits by using the catch per fisher as the outcome variable to allow comparison between pre-2005 and post-2005 management regimes.

Fishery catch data is publicly available from the California Department of Fish and Wildlife (CDFW) Marine Fisheries Data Explorer (MFDE). The data contains catch records from 1980 to 2024 at the port-complex and state level. Additionally, the data contains spatial records of catch with specified fishing blocks that can be used to refine the location of catch. I use this information to spatially match environmental variables as shown in Figure 2.1 for sea surface temperature. This procedure ensures that only the most relevant environmental data is used to predict fishery harvest in the models.

Market squid is a short lived species with a one year life cycle (Butler and Fuller, 1999). Sea surface temperature and upwelling primarily affect recruitment leading to large fluctuations in abundance by the time harvest occurs in the fall (Chasco *et al.*, 2022; Suca *et al.*, 2022). Year to year variation does not appear to persist removing dynamic considerations. This leads market squid to possess “corn-like” attributes akin to crops protected in agricultural index insurance. Planting cycles each year are independent from prior weather outcomes. A similar logic holds for market squid and allows the analysis to focus solely on contemporaneous weather effects.

Other independent variables demonstrate correlations to squid abundance. The Rockfish Recruitment and Ecosystem Assessment Survey (RREAS), conducted by the South-

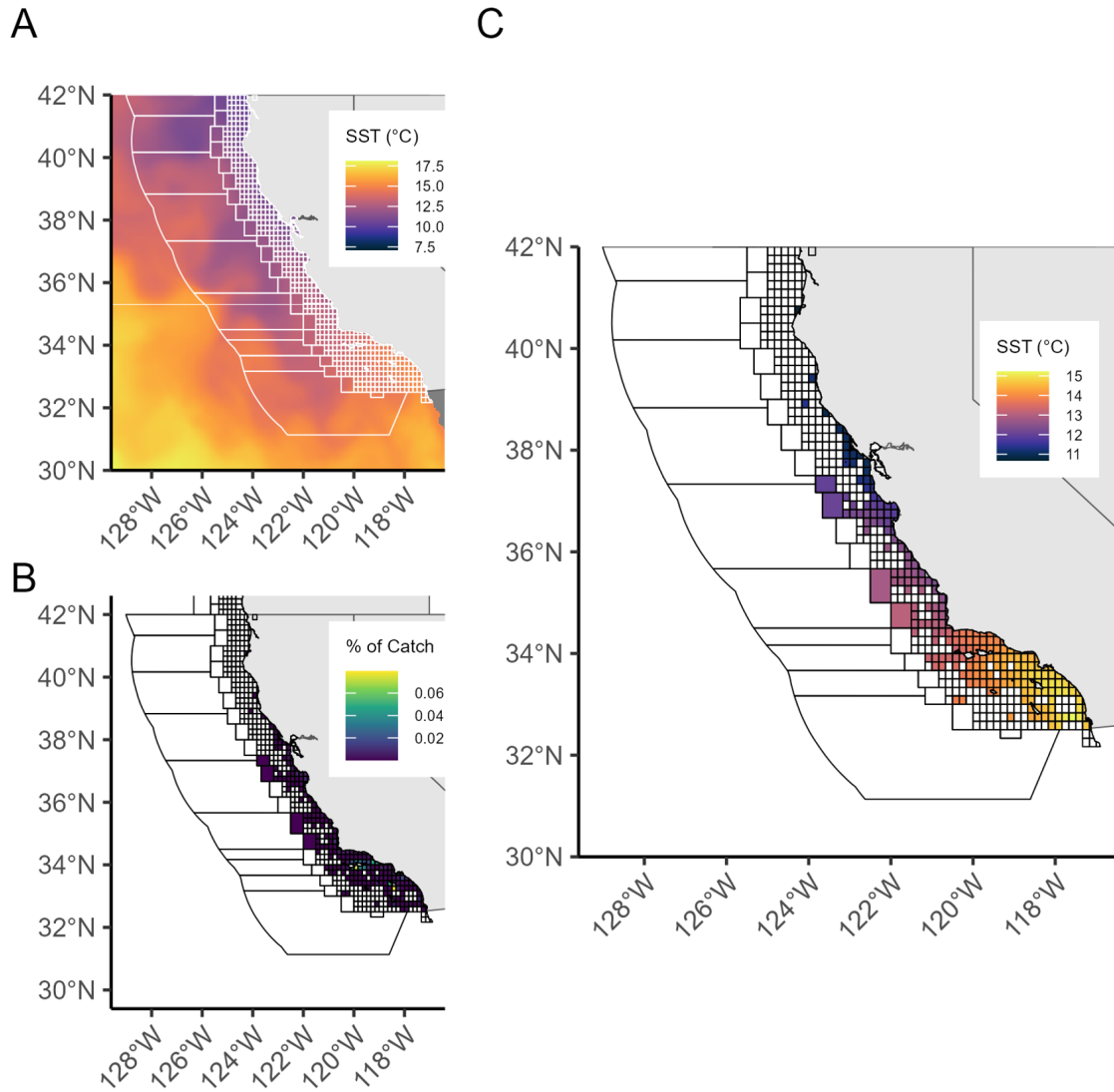


Figure 2.1: Demonstration of spatially matching catch data with weather variables. Panel A shows sea surface temperature at a 5km resolution. Panel B is the proportion of historical market squid catch by fishing block. Panel C is the intersection of fishing grids and weather variables. Sea surface temperature values are then averaged within each block, and the weighted sum by percent of historical catch is aggregated for each year.

west Fishery Science Center, provides independent surveys that collect tow samples that contain squid paralarvae and krill. Each of these metrics could be used by insurance companies to index fishery catch. Krill abundances are significantly correlated with fall landings (Ralston *et al.*, 2018). Paralarvae measures were the most important variable in random forest regressions to predict squid fishery catch (Allen Akselrud, 2024). These variables are also indicative of the potential to include non-weather variables that could serve as triggers.

2.5 Data

The dataset contains 34 annual observations (1990-2023) of squid catch per fisher and 12 weather variables. Catch histories extend to 1980, but to ensure a balanced dataset I limit observations to 1990, which is the earliest data available for squid and krill abundance in RREAS.

Fishery catch is publicly available through the California Department of Fish and Wildlife Marine Data Explorer (California Department of Fish and Wildlife, 2026). State wide catch is divided by the number of fishers to create metric tons of catch per fisher. Catch per fisher is detrended using a robust method of moments estimator. Detrending removes long term trends such as improved fishing technology, and any potential effects of the management shift in 2005 so that deviations from long run average are more directly attributable to environmental fluctuations. Observations are scaled relative to the last observed value to avoid negative values.

Environmental data to define indices are summarized in Table B.1. Descriptions of the sources of data and calculations are provided below.

Sea surface temperature data comes from the NOAA DHW dataset that provides 5-km resolution of monthly temperature from 1985 to 2023 (NOAA Coral Reef Watch,

2026). The 5-km grids are aggregated within the nearest California fishing block to provide an annual time series.

The Habitat Compression Index measures the area extent of water below average temperatures thresholds along the US West Coast (Schroeder *et al.*, 2022). Habitat compression is a measure of the spatial extent of cold water habitats that are important for fish species. The index is broken down into four distinct oceanographic regions ranging from 3.5 degrees to 5.5 degrees latitude in size with coverage out to 150 km offshore. I use the cumulative habitat compression index that sums the index value in each month to provide a yearly time series of habitat compression. The cumulative index showed stronger correlations with biological productivity measures than monthly measures (Schroeder *et al.*, 2022).

I use five different sources to define the strength of upwelling. Monthly observations of Coastal Upwelling Transport Index (CUTI) and Biological Effective Upwelling Transport Index (BEUTI) are averaged over the spring months of March, April, and May. Those months align most closely with squid egg mixing and dispersion. Both indices create measures of vertical movement in the mixed layer at 1 degree latitude intervals extending 75 km along the entire US West Coast (Jacox *et al.*, 2018). The closest layer to the surface was used in this analysis as the correlation between surface index values and deeper index values are high. CUTI examines the physical measures of wind, Ekman transport, and cross-shore geostrophic transport to indicate the strength of upwelling in a given month. BEUTI adds nitrate concentration in its calculation to capture biological effects of upwelling. Fishing blocks are matched to the nearest 1 degree latitude interval to provide a yearly time series of upwelling for each fishery.

In addition to direct measurements of upwelling, I characterize three upwelling events: Spring Transition Index, Relaxation, and Frequency following methods from (Suca *et al.*, 2022). Each variable was a significant predictor in Suca *et al.* (2022) recruitment models.

Spring transition is the date when the California Current transitions to a more stable upwelling system after the turbulent winter months. Mathematically, it is the first day of the year when the cumulative sum of BEUTI reaches its minimum value. Relaxation is the count of the number of days when CUTI exceeds $1.0 \text{ m}^2\text{s}^{-1}$ followed by three or more consecutive days of CUTI values $<0.5 \text{ m}^2\text{s}^{-1}$. Frequency is the proportion of days when CUTI is measured between 2.0 and $0.5 \text{ m}^2\text{s}^{-1}$. Frequency is indicative of moderate upwelling events that stimulate primary production without pushing production away from the coast.

Broader climate conditions have also been observed to impact squid abundance. The Pacific Decadal Oscillation (PDO) and El Niño Southern Oscillation (ENSO) have been linked to squid abundance (Perretti and Sedarat, 2016). ENSO has been used effectively in crop index insurance in Peru (Mortensen and Block, 2018). Larger climatic patterns may also be influential in squid recruitment. PDO data is taken from the PDO ERSST V5 dataset (National Centers for Environmental Information, 2026). One measure of ENSO data is taken from the multivariate ENSO Index Version 2 (MEI.v2) (Physical Sciences Laboratory, 2026b). The last measure is the Oceanic Niño Index (ONI) that is the 3 month running mean of ERSST.v5 SST anomalies in the Niño 3.4 region (Physical Sciences Laboratory, 2026a).

Squid paralarvae and krill abundance are calculated from the Rockfish Recruitment and Ecosystem Assessment Survey (RREAS). Midwater trawls sample yearly at various stations along the California coast. I use delta-generalized linear models to estimate log catch per unit effort of paralarvae and krill for the whole state in each year. Catch per unit effort serves as a proxy for prey and squid paralarvae abundance. RREAS does not have consistent temporal or spatial coverage. From 1983-2003, all surveys were done in a narrow window near Monterrey Bay. In 2004, more surveys locations were standardized into the Southern California Bight. Surveys were not conducted in 2014-2016 for the

southern stations due to budget constraints. Using catch per unit effort for all stations provides a useful statewide proxy.

2.6 Results

The multivariate models better predict environment-harvest dependency than univariate models (Figure 2.2). However, overfitting is a concern for the multivariate models. All multivariate models had lower RMSE than every univariate linear model in the training set (Panel A). In the test set (Panel B), multivariate models remained more accurate as a group, but the discrepancy between the types of models was much smaller. Support vector machine models had the lowest out of sample RMSE for the multivariate models followed by random forests, and then LASSO.

The best out of sample predictive model was frequency of upwelling events with the lowest RMSE out of all models at 265 mt per fisher. Two other groups of single weather indices performed well. Climate regional measures, (PDO, ENSO, ONI) had lower error in both the test and training sets than most other single variables. Krill abundance has the lowest RMSE in the training set, but had the highest RMSE in the test set out of all models.

The majority of univariate models made fishers worse off as shown by the decreases in relative utility (Figure 2.3 Panel A). Only three weather indices improved fisher utility: Upwelling frequency, relaxation of upwelling, and krill abundance. However, frequency and relaxation were unprofitable for insurance companies as each had a loss ratio greater than 250% (Figure 2.3 Panel B), which implies that insurance companies would have paid \$2.50 for every \$1 of premium collected. The upwelling indices paid large sums at times when fishers did not experience loss. The large payouts act more as wealth transfers than risk protection. Krill remained profitable for insurance companies with a loss ratio of

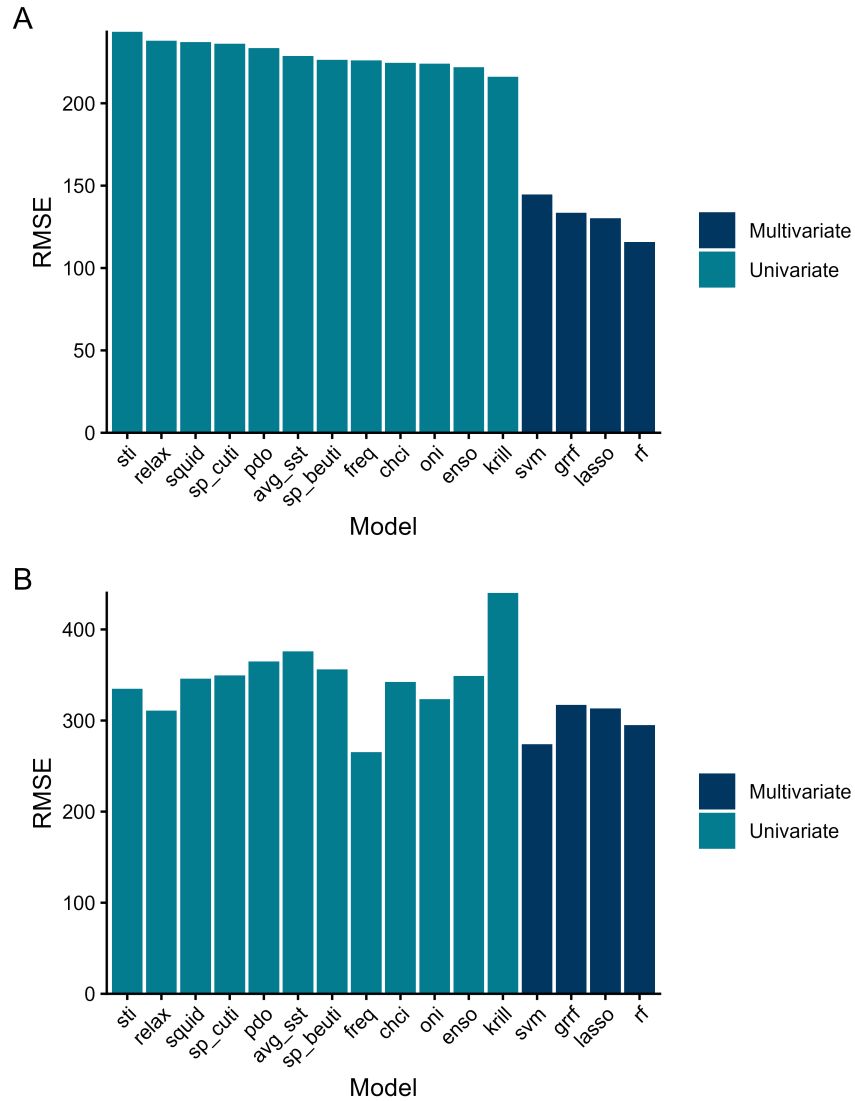


Figure 2.2: The Root Mean Square Error of weather models used to calculate insurance contracts. Panel A depicts the average RMSE across all training set windows. Panel B is the total RMSE in the test set using individual predictions from the rolling window. Model types are separated into single index univariate models (blue) and multivariate models (green)

55% at actuarially fair rates.

Every multivariate model improved fisher utility while reducing the insurance company loss ratio (Figure 2.3) compared to the univariate models. Contracts built with SVM and LASSO both improved fisher utility at actuarially fair rates, but each led to large losses for the insurance companies. Insurance companies remained solvent with both random forest models, and fishers experienced gains in utility.

The magnitude of percent change in utility is small (-.1% - 0.4%) primarily due to the choice of the risk aversion parameter. Examining fishers maximum willingness to pay through the market price captures the benefits of insurance contracts to the community than examining utility alone. I focus only on contracts that increased fisher utilities, otherwise significant subsidies would be required to stimulate demand. Figure 2.4 shows the market premium (m^*) an insurance company could charge at the upper limit of demand for each model in Panel A. For example, fishers would be at most willing to pay 60% higher than actuarially fair premiums for a contract built on SVM. On the lower end, fishers would be willing to pay 10% higher premiums for contracts using regularized random forests.

To ensure a feasible market could exist, insurance companies need to be profitable at levels fishers are willing to pay. Even at the upper limit of demand, insurance companies would not be profitable with the upwelling models and LASSO. The loss ratios remain above 1 implying insurance companies paid more out than they received at the market premium (Figure 2.4 Panel B). Despite the large willingness to pay for these contracts, insurance will not be willing to provide these contracts indicating an infeasible insurance product.

Fishers are most willing to pay for a contract with the support vector machine as it has the highest market premium loading factor. Insurance companies would be willing to provide contracts at the market premiums because the loss ratio is 0.89. Random

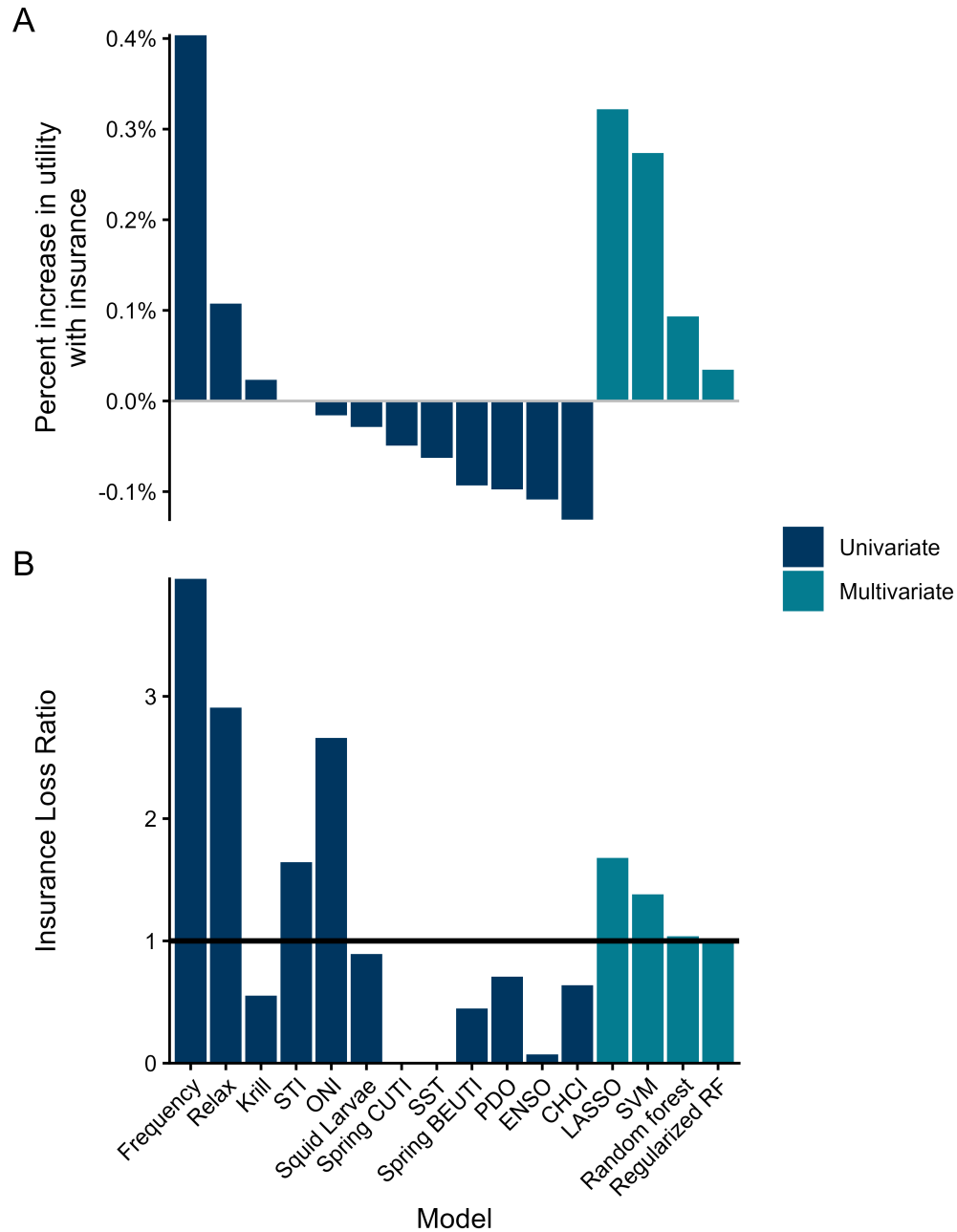


Figure 2.3: Percent increase in utility with insurance (Panel A) and the insurance loss ratio (Panel B) for each model using actuarially fair premiums. Models that fall above the horizontal line in Panel B are not profitable for insurance companies.

forest contracts are also profitable for insurance companies, though fishers are slightly less willing to pay for them. The accuracy of random forest to avoid false positives helps insurance companies avoid excessive payouts, allowing insurers to remain profitable even at lower market premiums.

I examine the payout and premium schedules over the testing period to understand how contracts improve utility. Univariate models payout less frequently (Figure 2.5 Right Panel). The krill index paid out once during the lowest catch year in 2019. Due to fisher risk aversion, fishers are more willing to pay higher premiums to protect against a single devastating loss (Figure 2.6). The upwelling indices pay more in later years. The frequency index pays out every year from 2018-2023 with the largest payout in 2020 (197 mt per fisher). These payout schedules correspond by chance to COVID-19 disruptions. However, the losses experienced by fishers are not driven by weather risk, but rather a coincidence that the upwelling indices predicted low catch during those years. The consistent large payouts lead insurance companies to significantly increase premiums as shown in Figure 2.6.

Multivariate predictive models initiate more frequent payouts, but payout larger quantities when fishers experience low catch (Figure 2.5). The flexibility of the underlying predictive models drives the payout schedule. However, with larger payouts, premiums must increase to compensate insurance suppliers. Premiums with multivariate models are high and remain consistent throughout the ten years of the test set (Figure 2.6). Contracts built with LASSO models differ the most from the other multivariate models. LASSO contracts pay out large sums in 2015 and 2023 when fishers experienced high catch. Insurance companies suffer losses in those years limiting profits even at the upper bound of market premiums.

The SVM and random forest contracts provide the largest utility gains while offering competitive market premiums. Overall, both models minimize downside risk for fishers

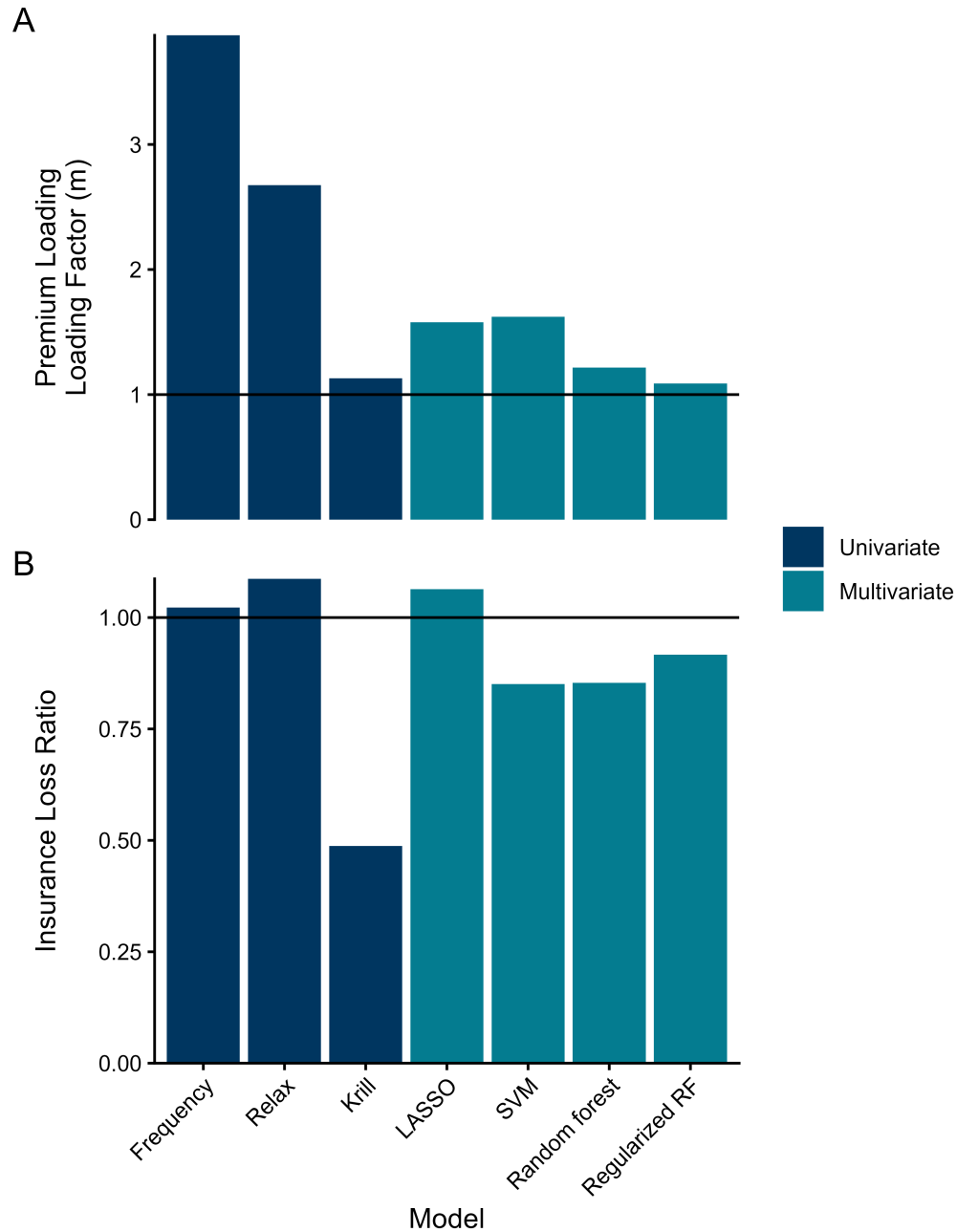


Figure 2.4: Market premiums rate (m^*) that make fishers indifferent between having insurance and not having insurance (Panel A). The corresponding loss ratio for contracts at the market rate is in Panel B. Univariate contracts are shaded darker than multivariate contracts.

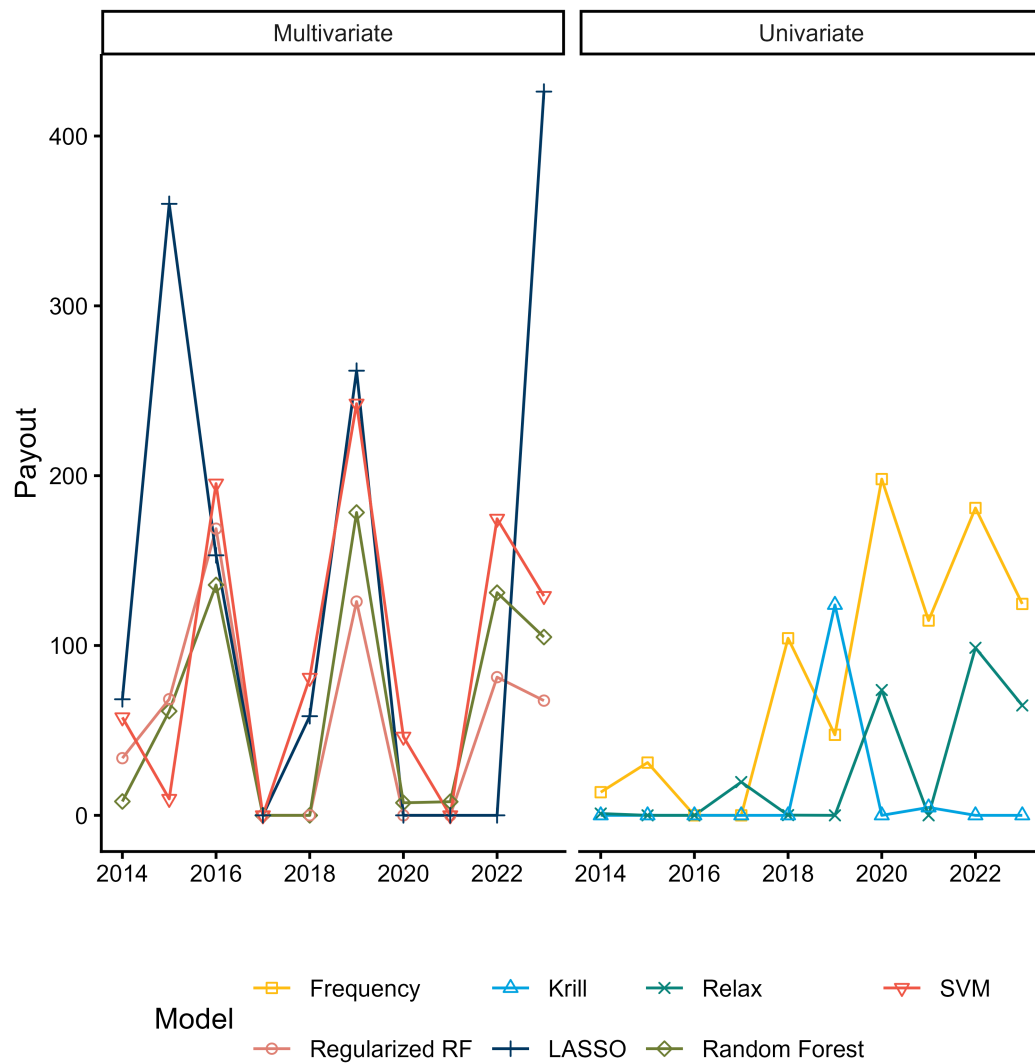


Figure 2.5: Payouts in the test set by each contract. Multivariate models (left panel) have more flexible payout schedules than utility improving univariate models (right panel). Individual models are colored and shaped by model type.

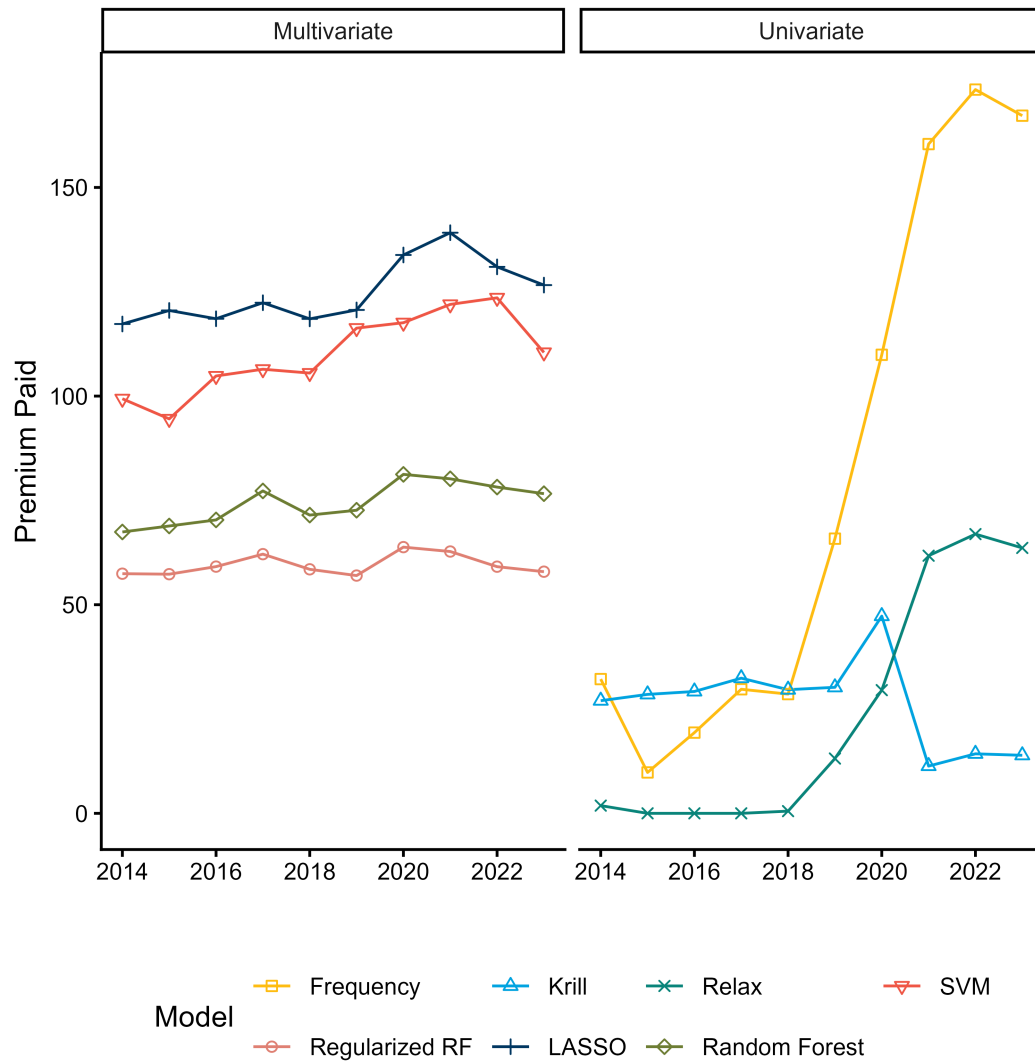


Figure 2.6: Premiums in the test set by each contract. Multivariate models (left panel) charge higher premiums to compensate for the more frequent payouts compared to univariate models (right panel). Individual models are colored and shaped by model type.

and insurance suppliers. There are two key differences in the performance of both models that are more easily observed when the net insurance payouts, payout minus the premium, is compared to the realization of fisher catch as shown in Figure 2.7. SVM contracts pay out more during down years compared to random forests. Larger payouts in periods of higher loss provide large gains in utility. The higher payouts lead to the corresponding higher premiums.

Random forests may be more accurate in identifying when to payout as the amount of false positives and negatives favors random forests compared to SVM. The notable exception is 2020 and 2021. Fishers experienced low catch primarily due to COVID-19 closures and market disruptions. COVID-19 was entirely independent of weather variables. Random forests paid a small amount in 2020 (7 mt per fisher) as weather indicators predicted a mild year in 2020. However, SVM paid out a larger amount (58 mt per fisher) in 2020. The large payout in 2020 was not necessary to protect fishers from weather risk, but it did provide significant utility gains as fishers were inadvertently protected from the COVID-19 disruptions.

2.6.1 Variable Importance

Multivariate models are more accurate, improve fisher utility, and viable in a private market. However, the payout schedule is determined by complicated, non-linear interactions. Frequency, ENSO, and krill were consistently the most important variables in the non-linear multivariate models Figure 2.8. Frequency became more influential across all models in later years. Sea surface temperature was important only within the random forests models.

I can evaluate ex-post whether my feature selection for random forests was accurate by comparing the variables of importance in the regularized random forest to those in

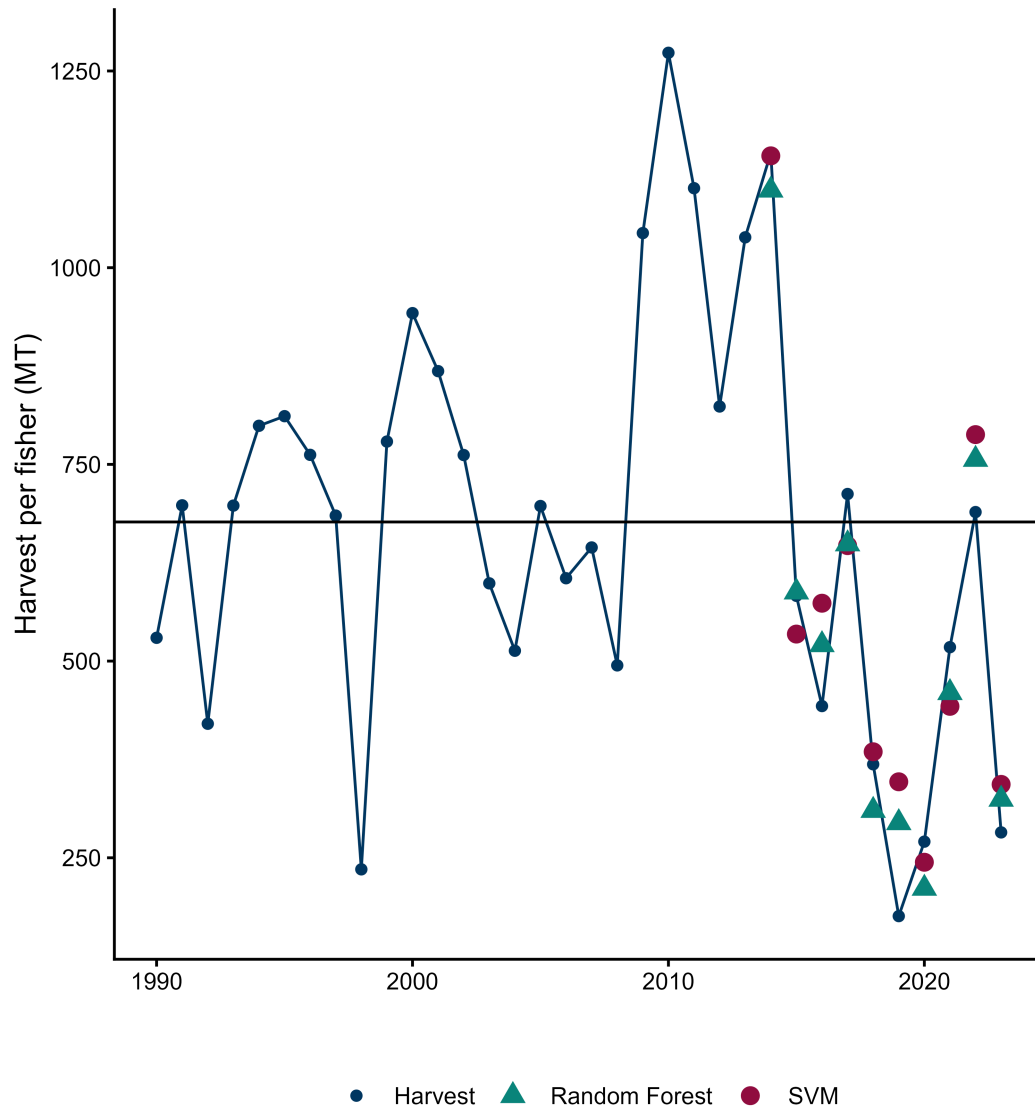


Figure 2.7: Net insurance payouts in the testing set (red points) from the SVM model and random forest (green points) compared to the detrended catch per fisher data from the California Market Squid Fishery (blue line and points). Insurance variables are in units of harvest per fisher. Horizontal black line is the average catch per fisher over the entire period.

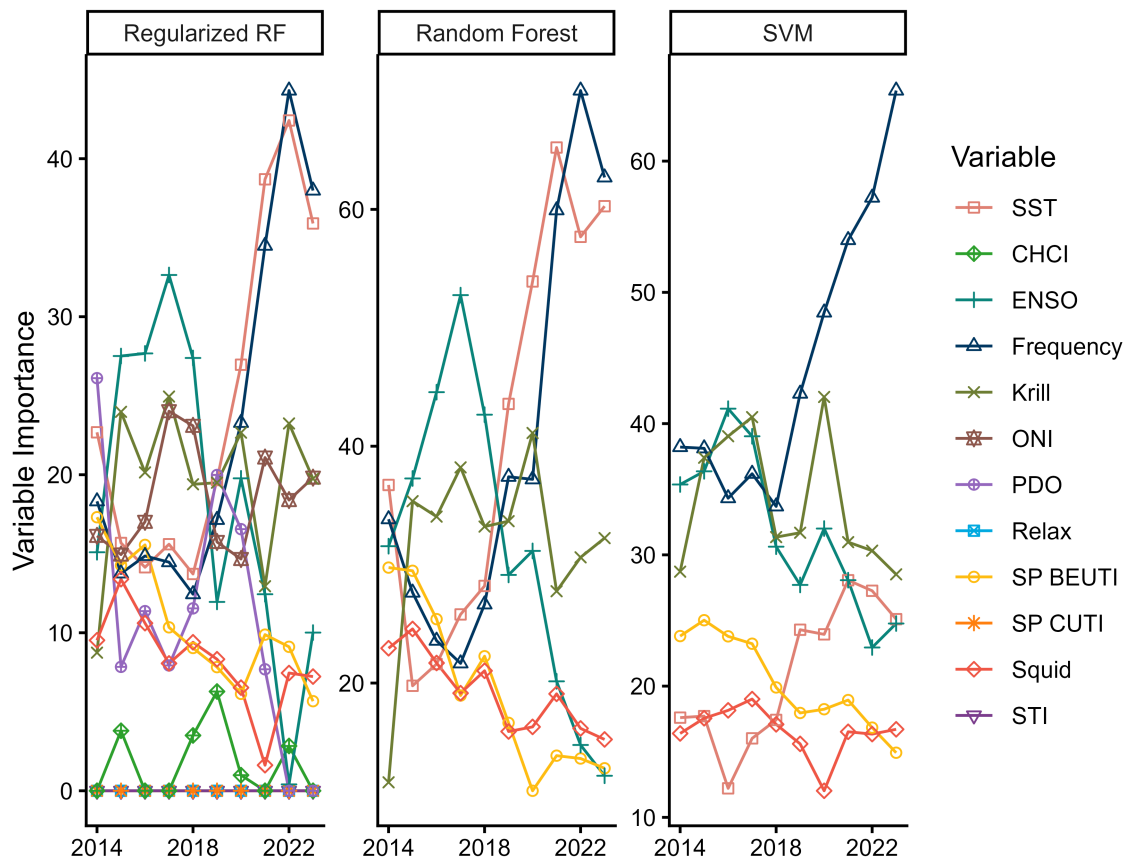


Figure 2.8: Variable importance from permutation for regularized random forest (left panel), random forest (middle panel), and SVM (right panel) in each iteration of the training window. Variables are colored and shaped by type.

the standard random forest. All measures selected based on expertise were included within the regularized random forest. The only missing information that was valuable in the regularized random forest were PDO and ONI. Perhaps more information could be captured with the inclusion of the other regional climate variables, but each are highly correlated and capture similar patterns. Overall, the feature selection based on correlation and expert knowledge was effective for both the random forest and SVM, and did not exclude any of the primary weather variables.

LASSO coefficients can be aggregated and divided by the absolute total to get a

measure of relative importance. Frequency is the most important variable in LASSO in all years comprising about 75% of the explanatory power of the model Figure 2.9. Spring CUTI was the second most important variable in all years followed by MEIv2 El Niño. Together, those three variables explained more the 90% of the models predictive power. A multiple linear regression contract with those three variables could increase predictive power beyond a single index while remaining clearly interpretable. However, given the lack of profitability for the overall LASSO it is unlikely that such a model would be market viable. The remaining environmental variables do not provide much additional value to the model. Spring Transition Index, PDO, Cummulative Habitat Compression Index (CHCI), and SST are dropped from the model during some training windows (Zoomed panel of Figure 2.9).

2.7 Discussion

Index insurance is feasible for the California Market Squid Fishery. Contracts built with a single index may be the preferred option as they are easy to implement and have clear, interpretable triggers, but the inconsistency of payouts is undesirable for both fishers and insurers. Only three indices out of twelve would have improved fisher utility over the last decade. Fishery productivity is rarely driven by individual weather patterns. It is unsurprising that using a single measure would provide sufficient risk protection.

Despite the preference for single index models, the performance of single index models is lackluster even in agriculture. For example, in the United States as part of the Rangeland, Pasture, Forage - Rainfall Index (RPF-RI) program rainfall to production correlations may be as low as 0.07 (Keller and Saitone, 2022). Significant subsidies are needed to support the RPF-RI due to the high levels of basis risk (Goodrich *et al.*, 2019). Other agricultural index insurance products do demonstrate improved utility for farmers

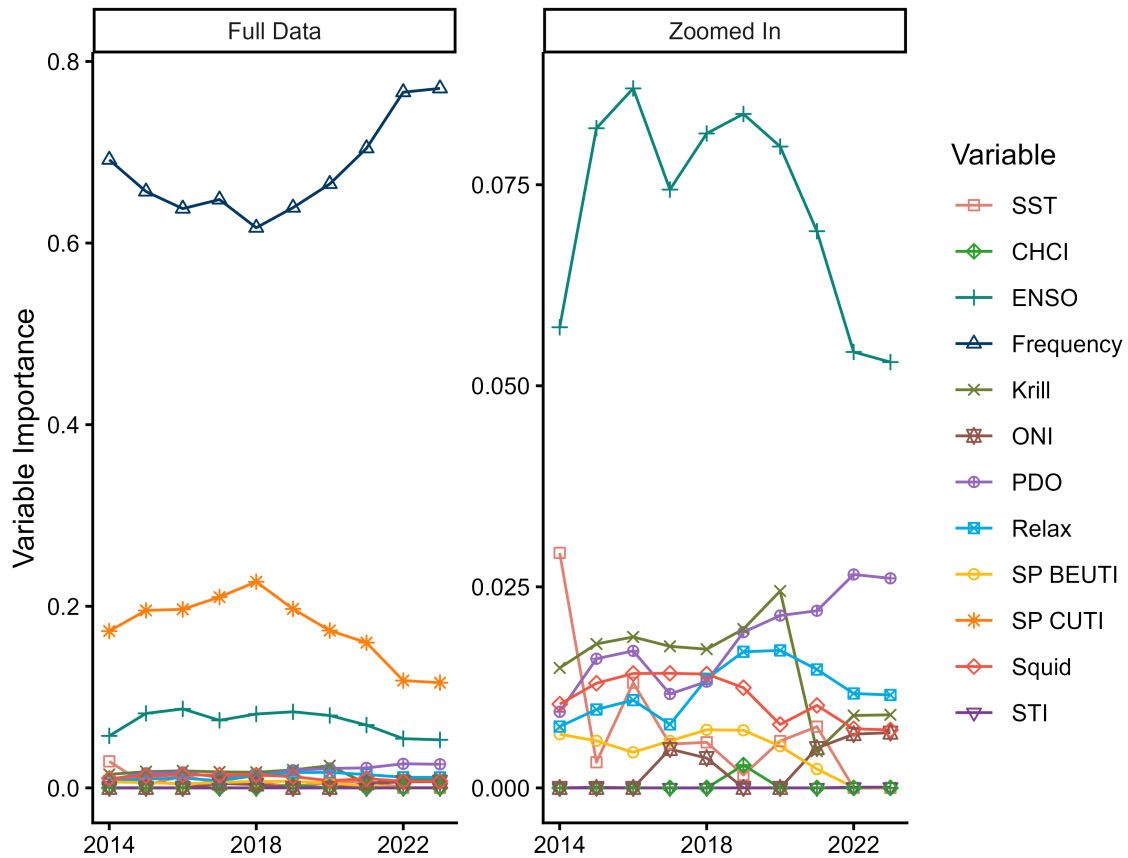


Figure 2.9: Relative importance of LASSO regression coefficients for each model trained in the training set. The right panel focuses on variables with less than 10% contribution. Variables are colored and shaped by type.

(Conradt *et al.*, 2015; Dalhaus *et al.*, 2018; Kenduiywo *et al.*, 2021), but few studies compare out of sample performance nor consider the supply side incentives of insurance companies (Chen *et al.*, 2024). Not assessing supply side viability may contribute to the low uptake of index insurance in agriculture and high premiums (Binswanger-Mkhize, 2012; Miranda and Farrin, 2012). For example, Kenyan farmers gain utility at actuarially fair rates for maize rainfall contracts, but lose utility at the commercial premiums (Jensen *et al.*, 2016). Single index fishery contracts demonstrate similar patterns that could prohibit effective deployment.

Machine learning models have been promoted as a response to the failures of single index agricultural index insurance (Cesarini *et al.*, 2021). Few studies have used machine learning to define weather-yield relationships, and as far as I am aware, no policy currently exists that uses multivariate machine learning models. Fishery machine learning models are market viable and provide large improvements to fisher utility. The model variable importance scores can help elucidate the “black-box” of machine learning models. The variables that were most predictive as single indices remained important in the multivariate models. Upwelling frequency, relaxation, and krill abundance were key explanatory variables in all models. Even though it is impossible to define a clear trigger for each variable in these models, explaining that these intuitive variables contribute the most to the determination of payouts will entrust fishers to the contracts.

Models with high basis risk often lead to high premiums. However, in this paper, the premiums fishers paid for multivariate models was higher than single index models. This phenomena originates from a unique form of data leakage that does not interfere with model performance, but does influence premium calculation. Nonlinear machine learning models accurately identify extreme losses in the training sets. Payouts in the training set will be much higher leading to more expensive premiums with standard burn rate pricing. Fishers are willing to pay these higher premiums as the multivariate models accurately

pay out large sums when necessary. However, this does emphasize the need to avoid overfitting as inaccurate out of sample predictions will lead fishers to pay high premiums without appropriate compensation when needed. All index insurance contracts that plan to use machine learning to identify weather to yield relationships will be affected by this phenomena.

A degree of overfitting is present in these models as the relative improvement in RMSE from the training set to the test set was diminished compared to the single index models. 2.2. Hyperparameter tuning and feature selection are essential to reduce overfitting. The rolling window strategy used in this paper demonstrates an effective way to limit overfitting and data leakage. The choice of which variables to include is important to reduce overfitting. Insurance actuaries will need to collaborate with fisheries scientists to narrow down the most suitable indices to include in multivariate models.

Defining the appropriate spatial coverage of indices and environmental variables is crucial for minimizing idiosyncratic basis risk. In agricultural index insurance, weather indices are interpolated between meteorological stations, which can produce situations where farmers within a grid cell suffer losses while the aggregate index fails to trigger. Fisheries appear less vulnerable to this form of basis risk. Fishers are more mobile and can respond to productivity shifts more readily than farmers, and squid productivity is driven by ecosystem-wide processes that tend to produce shared downturns rather than isolated winners and losers.

That said, accurately defining the spatial extent of environmental variables still matters. Here, I matched environmental variables to prior catch locations given the relatively localized boom-bust cycle of market squid, but the appropriate coverage will vary by species. For wide-ranging stocks like tuna, the relevant area spans ocean basins, and the appropriate monitoring region is far less obvious. For other species, a more refined spatial focus may be warranted. Well-documented spawning grounds near seamounts or

estuaries could yield more direct productivity signals than broader regional indices.

The choice of fishery is an essential component to expand index insurance. Each fishery is unique. Different environmental variables will be appropriate for fisheries outside of California Market Squid. Diversifying the index pool, spatially and ecologically, will allow insurance companies to diversify their risk more seamlessly than fishers are able. For example, insurance companies could create contracts for sea surface temperature in different ocean basins. The risk of a marine heatwave to strike both the California Current Ecosystem and the Gulf of Mexico is low. Additionally, species of fish react differently to environmental variables (Free *et al.*, 2019, 2023). Offering contracts that cover different species will spread out risk for insurance companies to avoid fund insolvency.

The selection criteria used in this paper to justify choosing California Market Squid for analysis is not restrictive, but does demonstrate some considerations that must be assessed when selecting fisheries for index insurance.

Fast growing species with short life cycles are more likely to be influenced by contemporaneous weather variables, and thus easier to empirically identify weather to catch relationships. However, longer lived species may also be insurable. The most important consideration is whether an environmental variable that influences catch can be identified. For example, Dungeness Crab have a four year life cycle. Environmental variables during the megalopae stage affect adult crab abundance and therefore harvest four years later (Shanks *et al.*, 2010; Magel *et al.*, 2020). If the variables are sufficiently correlated with catch, then an insurance contract could be designed based on environmental conditions four years prior.

An interesting consideration for the contract would be the timing of the payout. Should the contract pay out when the event occurs, or when fishers experience low catch? Paying out when the event occurs would provide fishers with more time to adjust their fishing strategies. However, the longer the lag between the event and the payout, the

more likely it is that other confounding factors could influence catch.

Management requires additional considerations. Well managed fisheries attempt to smooth biological risk by avoiding boom and bust cycles. Fishers remain vulnerable to fluctuations in management decisions such as quotas, season closures, or lost fishing days. These actions more directly impact fisher livelihoods than weather. Instead of designing contracts solely on weather variables, a new category of indices directly related to fishery management could be used. For example, quotas are set based on the underlying health of the fishery. An index insurance contract could use the quota as the index. This will provide a direct measure of lost catch for fishers while remaining an independent measure. Currently, insurance companies have demonstrated reticence on using management measures as they perceive management actions to introduce human influence. However, quotas are set based on rigorous scientific assessment outside the influence of fisher actions. The index would remain independent of policyholder influence, and is calculated in a transparent, objective manner.

Other triggers that originate from management could also be used. Days lost to fishing closures could be an index that more directly connects to fisher loss than environmental variables. Preseason salmon run strength predictions could be another. The exact nature and suitability require rigorous assessment and cooperation with management to ensure independence.

Improved catch predictions from machine learning models suggest similar gains are possible in stock assessments, where environmental factors remain largely absent from abundance estimates. A growing literature documents machine learning's capacity to sharpen management predictions, improve assessment accuracy, and refine harvest determinations. These results support those findings. All twelve weather variables in this study targeted weather events in the California Current Ecosystem months before the realization of harvest. Managers could incorporate this information to make more in-

formed decisions, and offer more responsive adjustments to harvest rules to protect the fish stock.

This paper demonstrates fisheries index insurance is feasible in a private market, but one-to-one application of techniques used in agriculture is unlikely to be successful. Assessing robust, new ideas will assist insurance companies in overcoming difficult empirical challenges unique to fisheries. Partnerships between fisheries scientists, economists, and insurance companies is essential to design effective contracts. As fishing communities face increasing environmental and economic uncertainty, index insurance provides a promising tool to help fishers remain financially resilient.

Chapter 3

Dynamic Index Insurance Induced Moral Hazard Effects on Fishery Harvest Control Rules

3.1 Introduction

Fishery management is the primary form of risk mitigation in fisheries (Lane *et al.*, 1998; Hilborn *et al.*, 2020). Managers act as social planners with long term visions whom coordinate efficient use of fish stocks to reduce the short run race to fish incentive (Munro and Scott, 1985). Healthier fish stocks arising from good management are more resilient to climate and weather shocks, generating sustainable and stable income for fishing communities (Pinsky and Mantua, 2014; Busch *et al.*, 2016; Lawler *et al.*, 2010). However, managed fish stocks are not immune to environmental shocks nor does management perfectly eliminate risk (Cheung *et al.*, 2018; Holsman *et al.*, 2019). When environmental shocks impact fishery productivity managers must close the fishery or significantly reduce quota in the short term to allow the population to recover. Restrictions on the

ability to fish generate enormous financial risk for fishers. Thus, friction exists between managers balancing the long term health of the fish stock with the immediate income needs of fishing communities (Parés *et al.*, 2015; Grainger and Parker, 2013; Kvamsdal *et al.*, 2016).

Index insurance could help reduce this friction by compensating fishers for losses stemming from closures or lower quotas due to environmental shocks. Additionally, management could curtail index insurance induced moral hazards that incentive greater harvest (Grimes *et al.*, 2026) by establishing binding constraints on fisher behavior. Fishers gain financial security with insurance, and management policies can still meet biological objectives without additional fishing pressure.

By relaxing constituent pressures to maintain higher levels of catch, index insurance may also change management policies. Fishers may be more willing to accept lower quotas if they have insurance to cover the loss. With this consideration, index insurance could incentivize managers to pursue more aggressive harvest control rules to protect fish stocks in the long run. Harvest control rules are set policies that determine the total available amount of catch after a stock assessment (Liu *et al.*, 2016; Free *et al.*, 2023).

This paper is the first to examine the influence of index insurance on fishery harvest control rules. I test whether a forward looking manager, who maximizes fisher total discounted utility, will change the optimal harvest control rule if the manager knows the insurance coverage decision of myopic fishers. In a simple two period model with complete uncertainty before the choice of quota must be made, insurance has ambiguous effects on the managers quota choice. Two countervailing forces drive this result. The first is the current period effect of insurance. A utility maximizing manager has the same incentive to increase quotas at all levels of biomass exactly as fishers in the myopic case of Grimes *et al.* (2026) with standard fishery production models. The second force arises as the manager considers the effect of insurance and risk in the future. Using simple growth

functions imply that variance increases with higher levels of stock. Therefore, insurance will protect against future variance, thus raising the shadow value of fish stocks. Higher shadow values of stock encourage managers to reduce fishing pressures now.

To estimate which force dominates, I solve the dynamic optimization problem with and without insurance using value function iteration. Insurance incentivizes managers to slightly increase quotas at low levels of the biomass state variable and slightly decrease fishing pressures at high levels. However, the magnitude of the insurance moral hazards for the manager are negligible.

Additionally, I take advantage of an information set unique to fisheries to determine how the timing of the quota announcement and the shock influence managers quota decisions. Fishery biological productivity is often impacted by environmental shocks that occur months to years before fishing occurs. For example, Peruvian anchoveta is highly correlated to ENSO cycles (Lehodey *et al.*, 2020). Anchoveta quotas are reduced by the Ministry of Production during El Niño years. Therefore, if an insurance contract is offered to fishers based on the independent measure of ENSO, the shock and payout is known to the manager before the quota decision. Under this information set in the two period model, the manager has a stronger incentive to reduce harvest even more knowing that fishers will be covered by insurance. However, during good states, managers have an incentive to increase harvest.

Solving for the optimal harvest control rules and using simulations with a representative fishery show that insurance contracts charged at actuarially fair and insurance provider favorable rates have little impact on long term community and ecosystem health. Subsidized insurance leads to pronounced conservation gains as the incentive to reduce harvest during bad shocks leads to healthier and more resilient fish stocks. Thus, subsidized insurance in combination with management can lead to conservation improvements while supporting long run community welfare.

3.2 Literature Review

Fishery managers use harvest control rules (HCR) to determine the total allowable catch each year to meet multiple biological and economic objectives (Punt, 2010; Liu *et al.*, 2016). The most robust HCRs determine set catch limits after a stock assessment quantifies the underlying biomass. The necessity of biological, catch, and economic data leads the formulation of HCRs to be expensive (Hilborn and Ovando, 2014; Bradley *et al.*, 2019). The benefits do outweigh the costs and fisheries that adopt robust HCRs have healthier fisheries (Mangin *et al.*, 2018; Costello *et al.*, 2012). To limit some of the challenge, most HCRs are modeled and determined under deterministic settings without considering risk nor uncertainty.

Uncertainty has notable impacts on optimal harvest control rules. Early linear control methods showed that constant escapement strategies remains the preferred policy under uncertainty of future stock growth (Ludwig, 1979). Whether the optimal escapement was higher or lower than the deterministic setting depends on the concavity of harvest costs (Reed, 1979). Different sources of uncertainty lead to more nuanced results. Stochasticity in the current period through measurement error or unobserved biological costs lead to optimal escapement levels that vary depending on the expected volatility of future recruitment (Clark and Kirkwood, 1986; Sethi *et al.*, 2005). In this uncertainty, output controls specifying harvest limits outperform input controls that specify effort (Yamazaki *et al.*, 2009).

More flexible and adaptive harvest control rules have arisen as the leading management tool to ameliorate uncertainty in stock arising from climate variability (Kritzer *et al.*, 2019; Pinsky and Mantua, 2014; Holsman *et al.*, 2019). The rapid response allows manager to more quickly adjust harvest to allow biological stocks to recover. However, the flexibility offered by responsive harvest control rules conflicts with risk averse fisher

preferences for more stable harvest.

While the various forms and impacts of uncertainty have been comprehensively studied in fisheries, few studies have integrated risk preferences of the manager or fishers in the determination of optimal harvest control rules (Andersen and Sutinen, 1984; Kelsall *et al.*, 2023). Risk aversion is a necessary condition for insurance to be desirable, thus necessitates its inclusion in this setting (François Outreville, 2014). Risk aversion leads to policies where quotas are set at more consistent levels regardless of the stock level (Lewis, 1981). Kelsall *et al.* (2023) used recursive risk preferences to isolate the impacts of risk aversion on optimal escapement into investment, wealth, and gambling effects. The risky nature of the stock encourages planners to set lower escapement to extract more now and invest in a risk free alternative.

Given that adding risk preferences is uncommon in dynamic fishery settings, insurance effects on harvest choices in a dynamic setting are not immediately clear. Insurance has been shown in static settings across fisheries (Grimes *et al.*, 2026) and agriculture (Horowitz and Lichtenberg, 1993; Smith and Goodwin, 1996; Mishra *et al.*, 2005; Deryugina and Konar, 2017; Ramaswami, 1993; Mahul, 2001) to either increase or decrease total production depending on the underlying risk characteristics of the production technology. In fisheries, standard production models are implicitly risk increasing which lead index insurance to increase harvest pressures Grimes *et al.* (2026). Those same production models are often used by managers to define HCRs. However, the increased fishing pressures would reduce fish stock health over time in opposition to management objectives of long term sustainability. Adding new policies without fully considering the dynamic effects could yield harmful outcomes especially in fisheries (Abbott and Haynie, 2012).

The agricultural insurance literature has a significant gap in identifying moral hazards in a dynamic setting. This paper is the first to use dynamic optimization to establish an optimal policy function with an environmental externality in the insurance field. Three

studies in agriculture consider temporal dynamics and pasture stocking levels with rainfall insurance, but none defined optimal policy functions. Bulte and Haagsma (2021) found that in a common-pool setting, index insurance will increase aggregate harvest. A social planner could limit the long run impact by setting the terms of the insurance contract. Bulte and Haagsma (2021) incorporated growth by analyzing the steady state equilibrium of insurance in the commons. Whether insurance will lead to improve sustainability depends on the initial steady state equilibrium grazing biomass. Müller *et al.* (2011) and John *et al.* (2019) also examined long run welfare impacts of index insurance in pasture grazing. In both studies, Kenyan pastoralists make herding decisions in response to observed weather shocks each year and contingent on a one time, perpetual insurance decisions at the beginning of the period. Insurance encouraged higher stocking levels that diminished long term pasture health in each study. The insurance moral hazard interaction with the stock externality degrades pasture health and long term gains of insurance.

The only study that solves for an optimal policy function in index insurance is Janzen *et al.* (2021). Here the authors test the effects of insurance to alleviate long run poverty by allowing small scale pastoralists to choose between asset savings, consumption, and paying for an insurance premium. There is no environmental externality so that pastoralists only make decisions based on the perceived productive of their assets. Insurance encourages households to invest more in the risky asset at lower asset levels. Insurance essentially helps break the liquidity trap of poverty and leads to more financially resilient household near the poverty line. Empirically these observations of increased capital investments or shifts towards riskier, but higher rewarding crops have been observed throughout the world (Stoeffler *et al.*, 2022; Sibiko and Qaim, 2020).

Total welfare gains of fishery insurance must consider the long term effect of insurance as fisheries given the highly dynamic nature of fish ecology. Managers act as the forward

thinking agent suitable for a dynamic optimization problem. In the next section, I build a simple two period model to uncover how the optimal harvest control rule changes with insurance.

3.3 Model

I construct a new dynamic model of manager harvest choices where myopic fishers have access to index insurance. Managers will choose quotas after measuring the available stock through a stock assessment. Fishers will observe the declared quota, which binds their harvest choices, but they may choose to purchase an insurance contract to protect against an environmental shock that impacts the standing stock of fish. To derive tractable analytical solutions in a two period model, I only focus the manager's choice of quota. The insurance contract will act as exogenous variable as the fishers choose the insurance coverage. When the optimal policy function is solved in section 3.4, I relax this assumption and allow an endogenous choice of insurance by fishers in response to the quota decision. The primary intent of this section is to sign any effects of insurance on the optimal harvest control rule of the manager.

3.3.1 Simple two-period

Consider a stock of fish that grows over two periods. A manager will choose quota (Q_t) in each period sequentially to maximize expected fisher utility with discount factor β :

$$\begin{aligned} \max_{Q_t} \quad & \sum_{t=0}^1 \beta^t \mathbb{E}[u(Q_t, (1 + w_t)b_t)] \\ \text{s.t.} \quad & b_{t+1} = G(s) \end{aligned} \tag{3.1}$$

The random weather shock, w_t directly impacts the current amount of fish available, b_t . Uncertainty stems from the random weather variable w_t that is distributed i.i.d with $\mathbb{E}[w] = 0$ and variance, $V(w) = \sigma_w^2$. The distribution of w_t is i.i.d with $\mathbb{E}[w] = 0$ and variance, $Var(\sigma_w^2)$, which are known to both fishers and manager. Biomass next period is b_{t+1} based on the residual escapement ($s = (1 + w_t)b_t - Q_t$). The growth function, $G(s)$, is increasing and concave in escapement ($G'(s) > 0; G''(s) < 0$). Utility is increasing and concave with $u'(\cdot) > 0$ and $u''(\cdot) < 0$. Growth occurs after the realization of the shock in period 1 so that the manager knows the available biomass in period two, but does not know the effect of a new shock in period 2. Notice that escapement is a decreasing function of current period harvest so that total growth is also decreasing in harvest, $\frac{\partial G(s)}{\partial s} \frac{\partial s}{\partial Q_1} < 0$.

Fishers derive utility from profits where revenue is the binding quota and costs are inversely dependent on stock and increasing in allowed harvest ($\partial c / \partial b_t < 0, \partial c / \partial Q_t > 0$). I assume fishers are a price takers and normalize price to 1:.

$$U(Q_t, b_t) \equiv \max_{\gamma_t} \mathbb{E} \left[u(Q_t - \frac{c \cdot Q_t}{(1 + w_t)b_t}) \right] \quad (3.2)$$

Insurance is offered privately to fishers each period, who chose a coverage rate γ . I assume managers know the fishers choice of insurance. Thus, to the manager, insurance coverage is an exogenous variable. The insurance contract pays the coverage rate, γ , for every step the realized weather shock is below the trigger, $\bar{w}$. Fishers must pay an actuarially fair premium, ρ , for access to the contract. Both the payout and premium are:

$$\begin{aligned} I(w) &= \max(\gamma(\bar{w}_t - w_t), 0) \\ \rho &= \mathbb{E}[I(w_t)] \end{aligned} \quad (3.3)$$

Insurance will amend the utility function in Equation 3.1 by including the payout and

premium terms. Working backwards from the second period where there is no future value of stock, the terminal period solution is:

$$V_2(b_2) = \max_{Q_2} \mathbb{E}[u(Q_2, b_2, w_2, I(w_2), \rho)] \quad (3.4)$$

The manager chooses the harvest level that maximizes expected utility given the biomass in the period that grew from the choice of the prior period. Knowing that she/he will choose optimally in the next period, the choice of harvest in the first period is given by:

$$V_1(b_1) = \max_{Q_t} \mathbb{E}[u(Q_1, b_1, w_1, I(w_1), \rho) + \beta V_2(G(s))] \quad (3.5)$$

I explicitly sub in the growth function for b_2 to more clearly show how future decisions are impacted by choices in the current period. From here, I consider two scenarios that demonstrate two possible information sets. The first is readily shown by Equation 3.5. This is the ex-ante scenario where the manager has to make decisions before the realization of the insurance payout. This represents cases when the weather index is revealed during the season¹

The second is ex-post where the shock and insurance payouts in the first period are revealed before the manager chooses fishing mortality. This represents cases where pre-season weather shocks that affect recruitment or productivity are known. The clearest example of this information set is the Peruvian anchoveta fishery. The strength of El Niño to anchoveta is well established (Lehodey *et al.*, 2020). Fishery managers will reduce harvest amounts if El Niño indicators show warm waters and minimal upwelling. If an insurance contract is specified on the multivariate El Niño Southern Oscillation

¹Agriculture is more often restricted to this information set. Farmers make a choice to plant or invest in livestock at the start of the year. Over the course of the year, weather randomly occurs impacting yield and the insurance payout occurs after the realization of said weather.

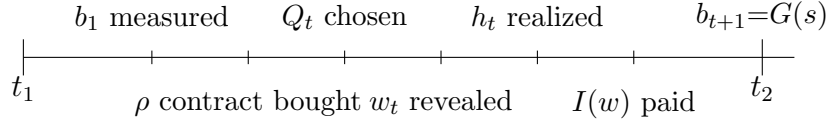


Figure 3.1: Ex-ante information set timing

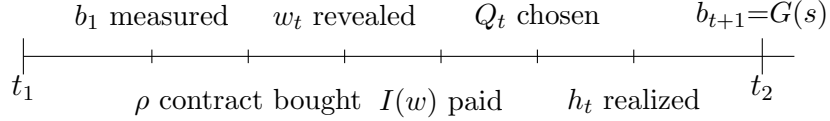


Figure 3.2: Ex-post information set timing

index (MEI.v2), than the managers would know if fishers will receive a payout before establishing quotas. I amend Equations 3.4 and 3.5 by replacing w_1 with a realized shock $\hat{w}_1$ and shift the expectations operator to the uncertain future:

$$V_1(b_1, \hat{w}_1) = \max_{Q_t} u(Q_1, b_1, \hat{w}_1, I(\hat{w}_1), \rho) + \beta \mathbb{E}[V_2(G(s), w_2)] \quad (3.6)$$

$$V_2(b_2, \hat{w}_2) = \max_{Q_2} u(Q_2, b_2, \hat{w}_2, I(\hat{w}_2), \rho) \quad (3.7)$$

The timing of both information sets is shown in Figures 3.1 and 3.2 to demonstrate when decisions are made and stochasticity resolved. For each information set, I will find the first order conditions then apply the implicit function theorem to sign the influence of higher insurance coverage.

3.3.2 Ex-ante choice

The first order conditions that solve Equations 3.4 and 3.5 respectively are:

$$\frac{\partial V(b_2)}{\partial Q_2} = \mathbb{E} \left[\frac{\partial u}{\partial Q_2} \right] \quad (3.8)$$

$$\frac{\partial V_1(b_1)}{\partial Q_1} = \mathbb{E} \left[\frac{\partial u}{\partial Q_1} + \beta V_2'(b_2) \frac{\partial G(s)}{\partial Q_1} \right] \quad (3.9)$$

The first order conditions in Equations 3.8 and 3.9 follow standard interpretations. In the terminal period, the manager will maximize fishers expected utility based on the observed biomass. The first period choice balances the marginal utility gain of fishing now with the shadow value of the future growth of residual fish stocks.

To determine the effect of insurance on these choices, I use the implicit function theorem to assess how a change in the coverage, γ , of the exogenous insurance contract will affect optimal choices of harvest. Due to the concavity of utility, variance reducing properties of insurance, and no basis risk, marginal utility is increasing with higher insurance payouts within the continuous set $[0, \gamma^*]$. Where γ^* is the payout that maximizes utility. Essentially, I am assuming an interior solution for optimal insurance exists otherwise purchasing insurance would not be welfare improving.

Applying the implicit function theorem to the first period first order conditions and rearranging leads to:

$$\frac{\partial Q_1}{\partial \gamma} = - \frac{\frac{\partial V_1}{\partial Q_1 \partial \gamma}}{\frac{\partial^2 V_1}{\partial Q_1^2}} \quad (3.10)$$

The denominator is negative by definition of the sufficient conditions of a maximization problem. Therefore, I examine only the numerator to sign the effect of insurance on optimal policy choices.

The numerator of Equation 3.10 breaks apart the effects of insurance additively in the current period and the future period as shown in Equation 3.11.

$$\frac{\partial V_1}{\partial Q_1 \partial \gamma} = \mathbb{E} \left[\frac{\partial u}{\partial Q_1 \partial \gamma} + \beta \frac{V_2'(G(s))}{\partial \gamma} \frac{\partial G(s)}{\partial Q_1} \right] \quad (3.11)$$

Insurance affects the direction of optimal choices of inputs through the risk characteristics of said inputs. Due to the additive separability of Equation 3.11 and linearity of expectations, I can isolate the expected change in marginal utility with a change in insurance by examining whether profit is risk increasing or decreasing in quota. For a full, formal proof of how risk increasing inputs lead to increased harvest with insurance, see Grimes *et al.* (2026). The insurance contract assumptions, utility form, and generality of production in each time period match the static setting of Grimes *et al.* (2026). Corollary 3.3.0.1 demonstrates that the quota is risk increasing, equal to other standard fishery production functions.

Corollary 3.3.0.1 *Profit is risk increasing in quota as $\frac{\partial Var(\pi)}{\partial Q_t} > 0$*

Proof:

$$\begin{aligned}
 \pi &= Q_t - \frac{cQ_t}{(1 + w_t)b_t} \\
 Var(\pi) &= \frac{c^2 Q_t^2}{b_t^2} Var\left[\frac{1}{1 + w_t}\right] \\
 Var(\pi) &\approx \frac{c^2 Q_t^2}{b_t^2} \cdot \frac{\sigma_w^2}{(1 + \mu_w)^4} \quad \text{By delta method} \\
 Var(\pi) &\approx \frac{c^2 Q_t^2 \sigma_w^2}{b_t^2} \quad \mu_w = 0 \\
 \frac{\partial Var(\pi)}{\partial Q_t} &\approx 2Q_t \frac{\sigma_w^2 c^2}{b_t^2} \\
 &> 0
 \end{aligned} \tag{3.12}$$

σ_w^2 is positive by definition of variance, and biomass and costs cannot be negative. Therefore, profit is risk increasing in quota. ■

The risk increasing properties of standard fishing production functions drive the effects of insurance on optimal harvest control rules leading to Proposition 3.3.1.

Proposition 3.3.1 *Index insurance effects on optimal harvest control rules are ambiguous in the ex-ante information set with standard risk increasing inputs as $\mathbb{E}[\frac{\partial u}{\partial Q_1 \partial \gamma}] > 0$*

and $\mathbb{E}[\beta \frac{V'_2(G(s))}{\partial \gamma} \frac{\partial G(s)}{\partial Q_1}] < 0$ in Equation 3.11

Proof: $\mathbb{E}[\frac{\partial u}{\partial Q_1 \partial \gamma}] > 0$ follows directly from Corollary 3.3.0.1 and the observation that the use of risk increasing inputs always increases with index insurance.

By the envelope theorem,

$$V'_2(b_2) = \mathbb{E}[\frac{\partial u}{\partial Q_2}]$$

Therefore,

$$\frac{\partial V'_2(b_2)}{\partial \gamma} = \mathbb{E}[\frac{\partial u}{\partial Q_2 \partial \gamma}]$$

$\mathbb{E}[\frac{\partial u}{\partial Q_2 \partial \gamma} > 0]$ as Q_2 is risk increasing through Corollary 3.3.0.1.

$\frac{\partial G(s)}{\partial Q_1} < 0$ as higher levels of harvest reduce escapement and thus growth.

All together:

$$\begin{aligned} \frac{Q_1^*}{\partial \gamma} &= \overbrace{\mathbb{E}[\frac{\partial u}{\partial Q_1 \partial \gamma}]}^{+} + \overbrace{\mathbb{E}[\beta \frac{V'_2(G(s))}{\partial \gamma} \frac{\partial G(s)}{\partial Q_1}]}^{-} \\ &\leq 0 \end{aligned}$$

■

Proposition 3.3.1 demonstrates there are conditions where index insurance incentivizes a resource user to lower input use, even with production functions that use risk increasing inputs. In the current period, insurance possess the same characteristics that lead to higher harvest in static settings shown by the first term of on the left hand side of Equation 3.11. However, insurance also increases the shadow value of fish stock. To see why, consider that the primary function of insurance is to reduce volatility. Variance increases with greater residual stock in the next period as growth is increasing in escape-

ment. Insurance then reduces variance leading to higher values of utility with higher levels of stock.

Higher harvest now lowers variance in the next period. Therefore, current period harvest is risk-decreasing in future production. Risk characteristics of inputs still matter greatly in dynamic contexts, but inputs now take on multiple possibilities. The intuition and logic remain the same.

Which effect dominates depends on multiple factors. The future term is inherently smaller due to discounting. However, the level of state variable will also influence the marginal value of insurance in the future. More stock increases the marginal value of insurance to protect against shocks so the future effect will be greater than the current insurance effect leading to lower optimal choices of harvest. On the reverse end, it may lead more harvest when the stock is in weaker condition. Paradoxically, this could trap the stock in persistent states of degradation. We will require numerical simulations to understand which effect, if either, outweighs the other.

3.3.3 Ex-post choice

In the ex-post scenario, managers estimate the current abundance and publish the information to insurers and fishers. In a private market before the shock occurs, fishers purchase insurance. Managers now choose current quota after the contract pays out, but remain uncertain on future states. The first order conditions of the ex-post equations are shown in Equations 3.13 and 3.14.

$$\frac{\partial V(b_2)}{\partial Q_2} = \frac{\partial u(Q_2, b_2, \hat{w}_2, I(\hat{w}_2))}{\partial Q_2} \quad (3.13)$$

$$\frac{\partial V_1(b_1)}{\partial Q_1} = \frac{\partial u(Q_1, b_1, \hat{w}_1, I(\hat{w}_1))}{\partial Q_1} + \mathbb{E} \left[\beta V_2'(b_2) \frac{\partial G(s)}{\partial Q_1} \right] \quad (3.14)$$

I examine how insurance will change the initial period decision of quota. As in the ex-ante case, I apply the implicit function theorem to the first period first order condition. The rearrangement is exactly equal to Equation 3.10. Signing the numerator as shown in Equation 3.15 will demonstrate the expected direction insurance will have in this information set.

$$\frac{\partial V_1}{\partial Q_1 \partial \gamma} = \frac{\partial u}{\partial Q_1 \partial \gamma} + \mathbb{E} \left[\beta \frac{V_2'(G(s))}{\partial \gamma} \frac{\partial G(s)}{\partial Q_1} \right] \quad (3.15)$$

Given that managers choose quota after the state is revealed, the first term in Equation 3.15 can be separated by states. By the linearity of expectations, the future period term is equivalent to the second term in Equation 3.11. As shown in Proposition 3.3.1, the second term will be negative reflecting the additional shadow value insurance adds to the fish stock by protecting against variance.

Proposition 3.3.2 *In the ex-post information set, with standard risk increasing inputs*

$$\frac{\partial u}{\partial Q_1 \partial \gamma} \leq 0 \text{ when } \hat{w} > \bar{w} \text{ and } \frac{\partial u}{\partial Q_1 \partial \gamma} < 0 \text{ when } \hat{w} < \bar{w}$$

Proof: Define the net payout function as:

$$N(\gamma) = \max(\gamma(\bar{w}_t - w_t), 0) - \mathbb{E}[I(w_t)]$$

When $\hat{w} > \bar{w}$: $\frac{\partial N}{\partial \gamma} < 0$.

And, $\hat{w} < \bar{w}$: $\frac{\partial N}{\partial \gamma} > 0$.

Expanding the first term of Equation 3.15:

$$\frac{\partial u}{\partial Q_1 \partial \gamma} = u''(Q_1, b_1, \hat{w}_1, N(\gamma)) \frac{\partial \pi}{\partial Q_1} \frac{\partial N(\gamma)}{\partial \gamma}$$

Concave utility implies the first term is negative. The future value remains negative

by the envelope theorem. The sign of $\frac{\partial N(\gamma)}{\partial \gamma}$ is contingent on the revealed weather variable.

When insurance pays out:

$$\begin{aligned} \frac{\partial u}{\partial Q_1 \partial \gamma} &= \overbrace{\frac{\partial u}{\partial Q_1 \partial \gamma}}^{-} \Big|_{\hat{w}_1 < \bar{w}_1} + \overbrace{\mathbb{E}[\beta \frac{V'_2(G(s))}{\partial \gamma} \frac{\partial G(s)}{\partial Q_1}]}^{-} \\ &< 0 \end{aligned}$$

When insurance does not pay out:

$$\begin{aligned} \frac{\partial u}{\partial Q_1 \partial \gamma} &= \overbrace{\frac{\partial u}{\partial Q_1 \partial \gamma}}^{+} \Big|_{\hat{w}_1 > \bar{w}_1} + \overbrace{\mathbb{E}[\beta \frac{V'_2(G(s))}{\partial \gamma} \frac{\partial G(s)}{\partial Q_1}]}^{-} \\ &\leq 0 \end{aligned}$$

■

Managers with information on the shock before the choice of quota have an unequivocal incentive to reduce harvest when shocks negatively impact the stock. Fishers are immediately protected from welfare loss by the insurance, lowering the need to provide quotas by the manager. Less fishing pressure allows the stock to recover more rapidly increasing the shadow value of the stock into the future.

When shocks are good, there remains a moral hazard incentive for the manager to increase quota in good conditions though the magnitude is dampened by the increase in future value of stock with insurance. The increased fishing pressures when the stock is boosted by favorable weather conditions may also act as a state substitution effect. Fishers are more tolerable of lower quotas in bad states with insurance knowing that the manager allows more aggressive quotas in good states. The resiliency of the stock remains strong so that the biological effects of increased harvest in the good states do not hinder sustainability objectives, whereas lowering the fishing pressures when the stock is most vulnerable provides large gains. Under this information set, index insurance provides the

ideal incentive strategy to improve conservation outcomes in fisheries.

One final observation is that the larger the payout gap, the stronger the behavioral effects on the manager. Premium subsidies could enhance the harvest reduction incentive by increasing the net payout term. In the following section we will test the effects of subsidies on the optimal harvest control rule to see if subsidies could be a useful tool to increase uptake while simultaneously increasing biological resilience through stronger behavioral effects.

3.4 Numerical Simulation

To numerically solve the optimal harvest control rule for the manager, I expand the two period model to an infinite horizon and endogenize the myopic choice of insurance by fishers. Escapement, utility, growth, insurance design, and profit remain equivalent to the two period setting. Quota remains binding, and the manager must publish the harvest control rule for any given level of biomass. Fishers choice of insurance coverage is a fixed point for any biomass and quota because the manager has to preemptively declare the quota. I assume managers know the response function of fishers to a given quota and biomass and internalize fisher insurance decisions into their calculation of the harvest control rule. The infinite horizon problem for the manager is Equation 3.16 to reflect the endogenous choice by fishers.

$$\begin{aligned}
& \max_{Q_t} \quad \sum_{t=0}^{\infty} \beta^t \mathbb{E}[u(Q_t, b_t, w_t, I(w_t, \gamma_t^*))] \\
& \text{s.t.} \quad \gamma_t^* \arg \max_{\gamma_t} u(Q_t, b_t, w_t, I(w_t, \gamma_t)) \\
& \quad b_{t+1} = G(s) \\
& \quad s = b_t(1 + w_t)(1 - h_t)
\end{aligned} \tag{3.16}$$

I can reformulate Equation 3.16 as a Bellman Equation in Equation 3.17 as the ex-ante case.

$$V(b_t) = \max_{Q_t} \mathbb{E}[u(Q_t, b_t, w_t, I(w_t, \gamma_t^*)) + \beta V_{t+1}(G(s))] \quad (3.17)$$

The ex-post Bellman shifts the expectations operator in Equation 3.17.

$$V(b_t) = \max_{Q_t} u(Q_t, b_t, w_t, I(w_t, \gamma_t^*)) + \mathbb{E}[\beta V_{t+1}(G(s))] \quad (3.18)$$

Value function iteration solves the managers Bellman equations (Equations 3.17 and 3.18) internalizing fishers choices of insurance. The stochastic environmental variable w is discretized from a continuous normal distribution with $\mathbb{E}[w] = 0$ and variance $\sigma_w = 0.2$ into a stationary marginal distribution through a quadrature-based discretization with $n_w = 15$ bins. Within each expectation calculation in Equations 3.17 and 3.18, the utility at each grid point is calculated then weighted by the probability masses and summed.

I use a negative exponential utility functional form to represent constant absolute risk aversion. Negative exponential utility is preferred because it remains defined for negative values that may occur when managers close the fishery while fishers simultaneously pay premiums without receiving a payout. I set three coefficients of risk aversion to represent low, mild, and high risk aversion ($\alpha \in \{0.003, 0.03, 0.3\}$) to test the effects of fisher risk aversion on the purchase of insurance and the managers optimal control rule that internalizes fisher risk preferences ².

Insurance coverage is an endogenous choice variable that fishers optimize myopically given each allowed quota and observed biomass. I test multiple contract structures that vary the premium loading factor, $m \in \{-0.5, 0, 0.05\}$, and trigger, $\bar{w} \in \{-.01, -.15\}$.

²Given the carrying capacity of 100, the maximum profit earned is about 60. Thus the CARA risk coefficients roughly correspond to constant relative risk averse coefficients of 0.18, 1.8, and 18 respectively. at the highest available profit margins.

Subsidized insurance premiums match the lowest rates offered by the existing RF-PRF policy for ranchers in the United States. I focus solely on fisher utility, so the subsidies are paid exogenously. Total societal welfare would need to consider a more general tax base. For now, I focus on the immediate impacts to the fishing communities. Actuarially unfair premiums allow insurance companies to earn a gross profit margin of 5%, in line with other insurance products. Premiums greatly affect demand and desirability of insurance, thus leading to different behavioral responses.

Stock growth is the standard logistic growth function:

$$G(s) = s + r * s(1 - s/k) \quad (3.19)$$

where $r = 0.8$ is the intrinsic growth rate and $k = 100$ is the carrying capacity.

3.4.1 Ex-ante harvest control rule

In the ex-ante case, the manager is able perform a stock assessment on the current stock of biomass, but is aware of potential future environmental shocks that may impact fishers ability to harvest or the health of the underlying stock before harvest. Insurance does not change the harvest control rule under the ex-ante information set (Figure 3.3). The two countervailing forces of Proposition 3.3.1 balance out. Additionally, there are two other considerations that help explain the lack of change. First, a large piece of the value of insurance comes from the relaxation of risk to expand production. With binding quotas, the immediate value of insurance is reduced as fishers cannot increase production with the purchase of insurance. Second, the intertemporal elasticity of substitution is identical to risk aversion under the expected utility framework. The marginal value of insurance is relatively small (2-10% increases in utility in Grimes *et al.* (2026)) in static settings. In a dynamic setting, small marginal changes in the extraction of the fish stock

carry much stronger weight in the optimization decision.

Fisher choice of coverage level is contingent on the publicly available biomass measurement, risk aversion, and premium loading factor. Subsidized premiums encourage fishers to purchase the maximum available insurance coverage at all levels of biomass (Figure 3.4). Fishers with high risk aversion will always purchase insurance, but at a rate less than full coverage. Downside risk even with subsidized insurance is more prevalent with higher risk aversion, similar to that found in Clarke (2016). Policies with actuarially fair premiums are only purchased when biomass levels are sufficiently high. Insurance protects against fisher income risk. When the manager sets harvest to zero, fisher income enters an edge case where there is no volatility. Without volatility, insurance provides no value so fishers will opt out of purchasing insurance. As the manager increases allowable catch at higher levels of biomass, fishers will choose to purchase insurance.

The decision to not purchase insurance may also drive the lack of change in the harvest control rule by the manager. If fishers do not purchase actuarially fair insurance, there is not incentive for the manager to change the HCR.

Risk aversion increases the value of insurance. At high risk aversion, actuarially fair and provider-favorable premiums are bought for all levels of biomass above a quarter of the carrying capacity. For low risk averse individuals, actuarially unfair insurance is never purchased.

3.4.2 Ex-post harvest control rule

The harvest control rule in the ex-post information set is now a function of the realized shock and the observed biomass. While there are n_w states from the discretization, I present the results as the weighted average policy function between the states where the manager knows the insurance will pay out and when the insurance does not pay out. The

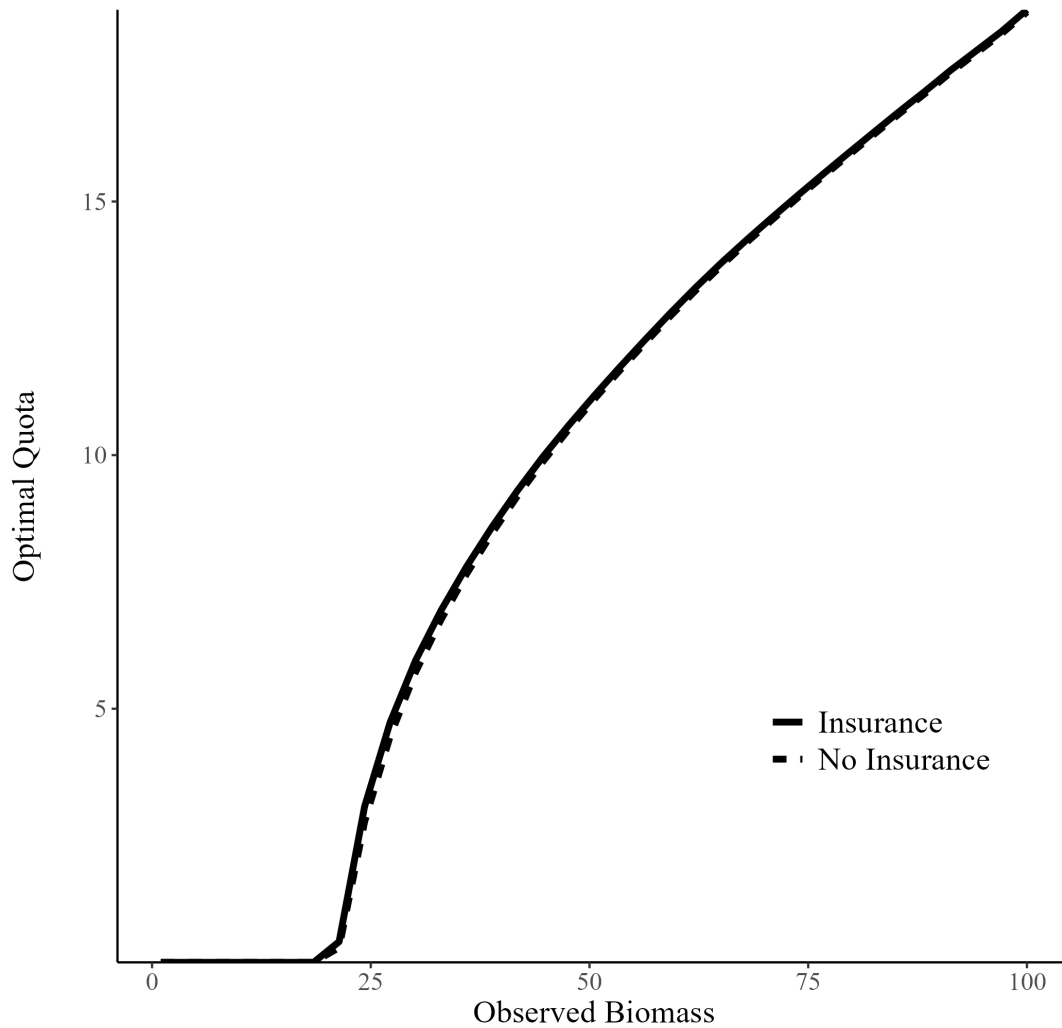


Figure 3.3: Harvest control rule with ex-ante information information set. Solid line indicates the optimal choice of quota (y-axis) for a given level of biomass (x-axis) with insurance, while the dashed line indicates no insurance. Due to the minuscule differences in policy, the lines overlap and look identical.

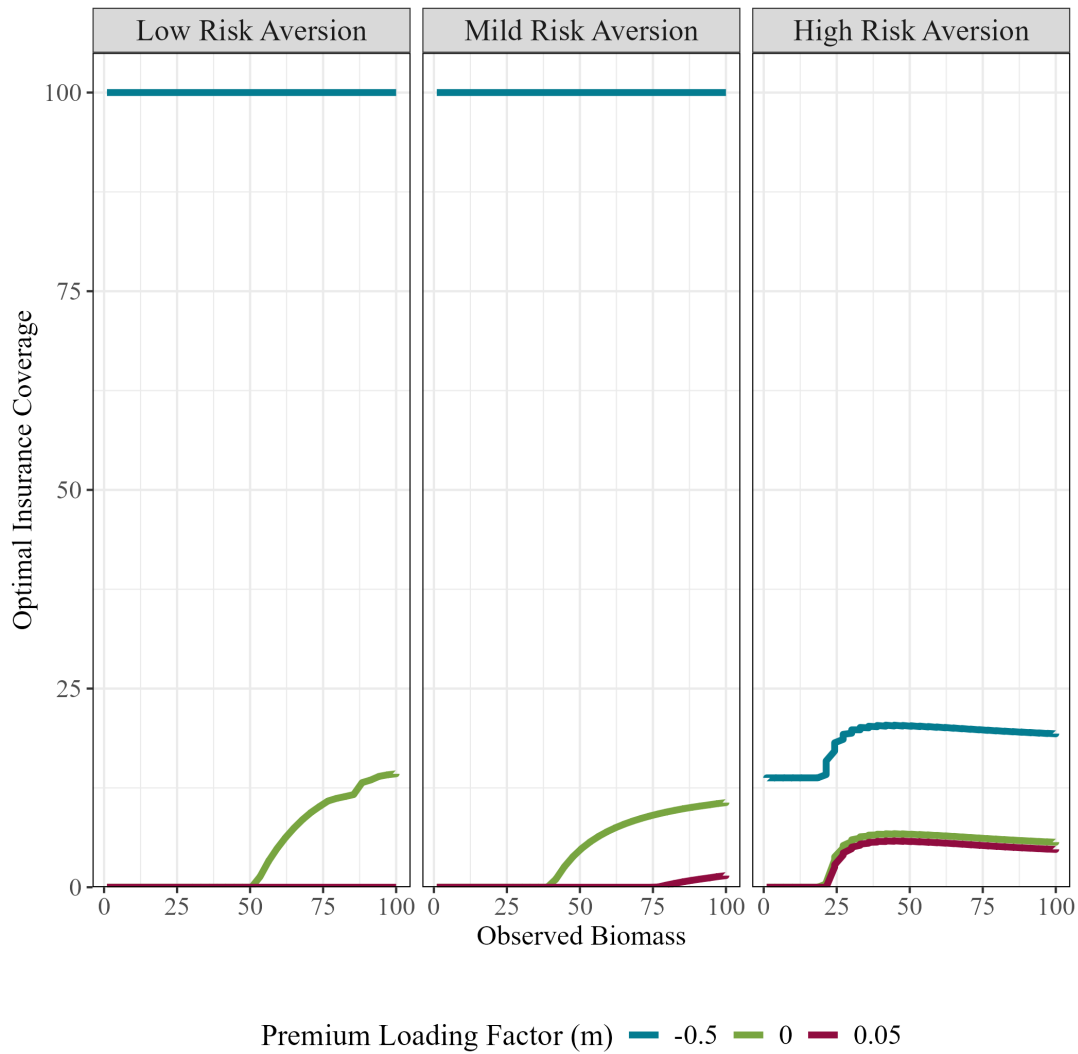


Figure 3.4: Fisher choice of insurance coverage at low (left panel), mild (middle panel), and high (right panel) levels of risk aversion for any given level of biomass. Premium loading factors are colored with blue lines indicating largely subsidized rates, green actuarially fair, and red showing a markup of 5%

effect of insurance on the optimal harvest control policy remains small for actuarially fair and provider-favorable premiums (Figure 3.5).

Subsidized premiums induce the greatest change in the manager's choice of quota (Figure 3.6). When managers know fishers will be protected by subsidized insurance policies, the manager reduces quota allowing the stock to recover following a negative shock. The reduction in quota can reach 25% at the highest levels of biomass. Quota increases during positive shocks are consistently much lower than the reductions during negative shocks.

Insurance coverage consumption is nearly identical in the ex-post information set as the ex-ante (Figure 3.7). Shocks remain unobserved for fishers, otherwise fishers would choose to only purchase insurance only when payouts are known and opt out otherwise. Given they can only form an expectation around what the manager could suggest as quota for an observed biomass, their decision mostly remains the same. The most apparent difference is the willingness to purchase provider-favorable premiums under mild risk aversion increases for higher levels of observed biomass. Fishers may be more willing to take on risk downside knowing that if a bad shock occurs the manager will adjust quota in addition to the insurance payouts.

3.4.3 Forward Simulations

To test the impact of index insurance on the sustainability and long run welfare of fishing communities, I sample random weather shocks over 30 years across 1000 simulations. Managers use the defined harvest control rules to set quotas in each year. Fisher choose insurance following the optimal insurance coverage rules. The stock grows after harvest according to Equation 3.19. I set initial biomass to half of carrying capacity. The harvest control rules are all conservative for low biomass so that changing initial

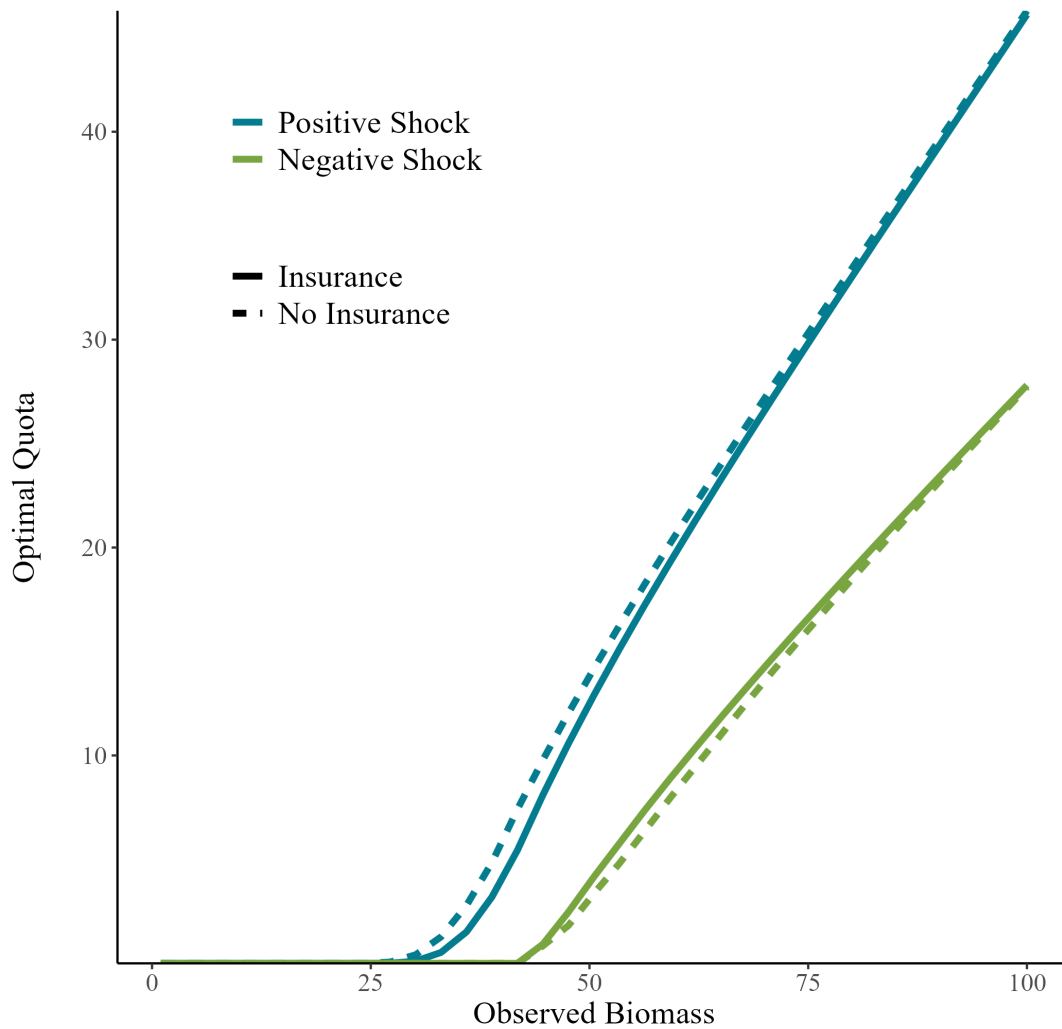


Figure 3.5: Harvest control rule with ex-post information information set with actuarially fair insurance $m = 0$. Solid line indicates the optimal choice of quota (y-axis) for a given level of biomass (x-axis) with insurance, while the dashed line indicates no insurance. Blue lines show the weighted average policy for shocks that are greater than the trigger $\bar{w}$, while green lines show the weighted average policy for shocks below the trigger $\bar{w}$.

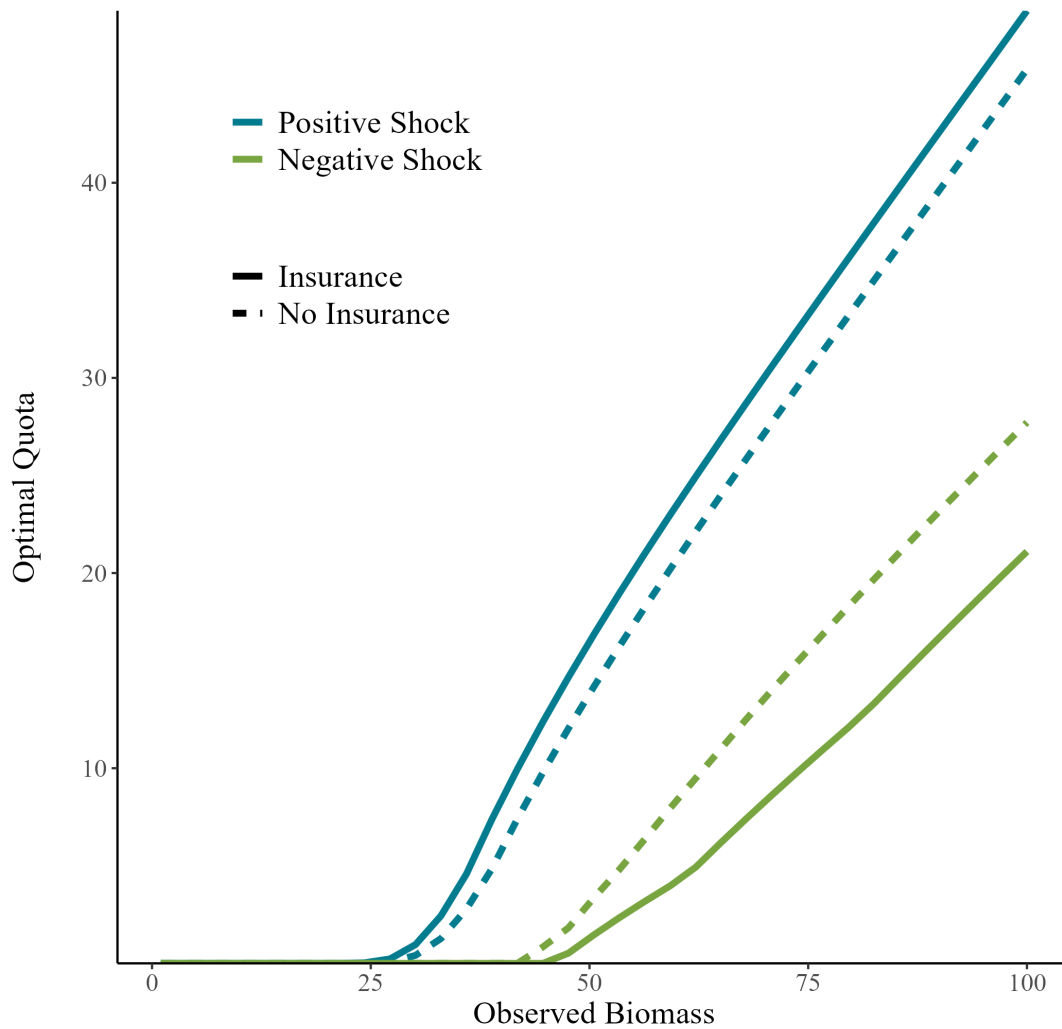


Figure 3.6: Harvest control rule with ex-post information information set with subsidized premium $m = -0.5$. Solid line indicates the optimal choice of quota (y-axis) for a given level of biomass (x-axis) with insurance, while the dashed line indicates no insurance. Blue lines show the weighted average policy for shocks that are greater than the trigger $\bar{w}$, while green lines show the weighted average policy for shocks below the trigger $\bar{w}$.

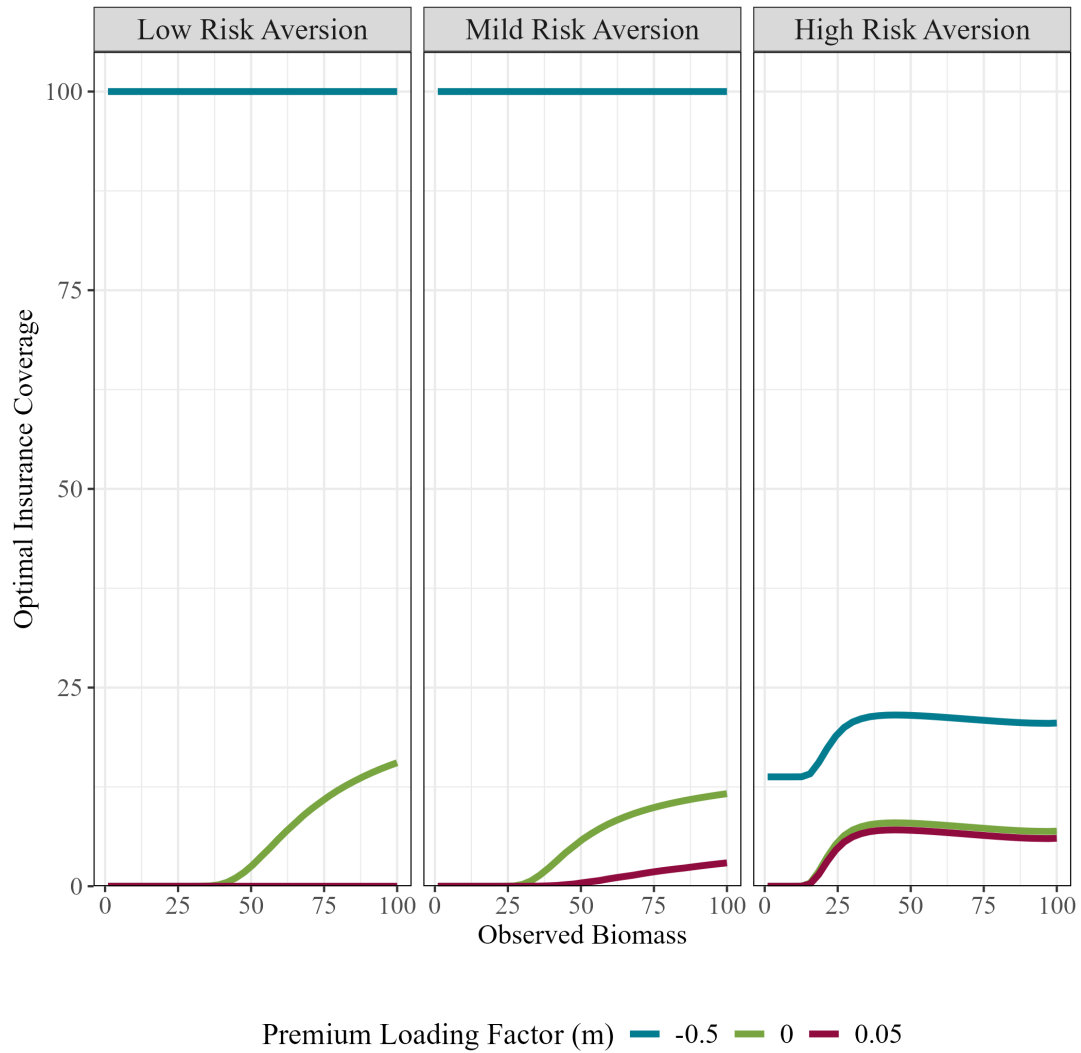


Figure 3.7: Fisher choice of insurance coverage at low (left panel), mild (middle panel), and high (right panel) levels of risk aversion for any given level of biomass in the ex-post information set. Premium loading factors are colored with blue lines indicating largely subsidized rates, green actuarially fair, and red showing a markup of 5%

biomass only impacts total welfare, but provides little comparative difference between harvest control rules.

I calculate total discounted utility across the 1000 simulations to compare community long run welfare with and without insurance. I use the last observed biomass at the end of 30 years as a measure of ecosystem health. The aggressive closures for low biomass consistent across all optimal harvest control rules implies extinction rarely occurs regardless of the insurance decision.

The small differences between harvest control rules in the ex-ante information set do not lead to large differences in utility (Figures 3.8 and 3.9) or ecosystem health (Figure 3.10). Utility gains at actuarially fair and provider-favorable premiums are imperceptible compared to no insurance. However, if the premiums are subsidized the insurance community is distinctly much better off. Those gains are only from the wealth transfer of the premium and not from any gains to biomass.

Insurance in the ex-post information set lead to more distinct changes in ending level biomass due to the more pronounced changes in the harvest control rule (Figure 3.13 and Figure 3.14. The weak increases of quota during low shocks lead to a slight shift to the left of the distribution of final biomass at actuarially fair premiums. Overall, the changes from insurance are small and do not promote long term degradation when combined with an optimal policy function compared to other instances that examined the dynamic effects of insurance. Subsidies lead to distinct improvements in biomass. The average final biomass increases by $\sim 7\%$. The spread of biomass is also greatly reduced, presenting a more resilient ecosystem if fishers are protected with subsidized insurance. Reductions in quotas during harmful shocks greatly stabilizes the system.

Long term welfare for the community is relatively unchanged at actuarially fair and provider-favorable premiums (Figures 3.11 and 3.12). Subsidies increase discounted util-

ity as before in the ex-ante set through a wealth transfer, but there are additional gains to utility from the higher levels of stock as it leads to higher, more consistent levels of catch across time periods.

3.5 Conclusion

Index insurance has the potential to incentivize fishery managers to adjust harvest policies to more favorably protect fishery resources, though it requires prior information on the shock and subsidized premiums. Otherwise, the effects of index insurance on the long term health of the stock and community welfare are negligible suggesting insurance could be offered without adverse effects though the gains may not be as lucrative as intended.

The small effects of insurance may arise from the management crowding out risk mitigation. Risk aversion and intertemporal elasticity of substitution are inseparable in an expected utility framework. Quota decisions more directly account for intertemporal substitution by explicitly controlling the value of future harvest limits. Given that the marginal value of an additional unit of stock is compared to additional insurance unit in actuarially fair settings, the quota decision dominates the insurance decision. Distinguishing a more direct impact of uncertainty into a dynamic optimization framework through recursive preferences may allow for clearer analysis of insurance impacts. Insurance could alleviate risk while management actions account for fisher preferences for smoother catch limits. The value of insurance and its effects may be stronger.

While a private market is feasible at actuarially fair and unfair rates for highly risk averse fishers, subsidies may be necessary to avoid a dynamic selection bias and promote conservation. Fishers only purchase actuarially fair and provider-favorable premiums at sufficiently high stock for all levels of risk aversion. Fishers always purchase insurance

with subsidies. This will allow for less fluctuations in insurance contracts each year as fishers always buy in. Subsidies have arguably been necessary for index insurance uptake in agriculture (Binswanger-Mkhize, 2012; Goodrich *et al.*, 2019; Clement *et al.*, 2018), thus the usefulness of subsidies to stimulate demand is unsurprising. Providing more consistent insurance uptake each year due to the productivity dynamics is a new insight. Contract design could also prevent fishers from explicitly choosing no coverage during low biomass periods. Offering contracts for triggers over the course of years is one way to avoid a temporal selection bias.

Premium subsidies encourage managers to reduce fishing pressure during negative shocks if managers know fishers will receive insurance payouts. In this instance, subsidies act similarly to indemnified payment for ecosystem services. Subsidized insurance is more cost effective than straight payment for ecosystem services. This paper assumes the general public foots the subsidy bill. Currently, tax payers in the United States already subsidize fisheries through \$2 billion dollars over 20 years in diaster relief payments (Bellquist *et al.*, 2021). The system is inequitable, slow, and becoming increasingly unpopular as it requires congressional approval to disburse funds (Upton, 2013; Jardine *et al.*, 2020). Subsidized insurance could provide a more effective and objective way to deliver funds to fishers in need of relief. Agriculture originally used a similar disaster relief program before transitioning to crop insurance program used today in the 1980 Farm Bill (Goodwin, 1993; Glauber, 2004). Federal crop insurance premiums annually cost taxpayers \$12 billion dollars. Complete coverage of fisheries will not reach those levels as the relative value of fisheries is drastically less, but even at the lowest premium rates modeled in this paper, insurance could incentivize 25% reduction in harvest promoting healthier, more resilient fish stocks.

Index insurance remains an exciting tool for application in fisheries. The long term maladaptive effects of insurance are mitigated when combined with effective management.

The question to subsidize insurance remains open and requires a wholesale analysis of the cost effectiveness to the current use of reactive diaster payouts.

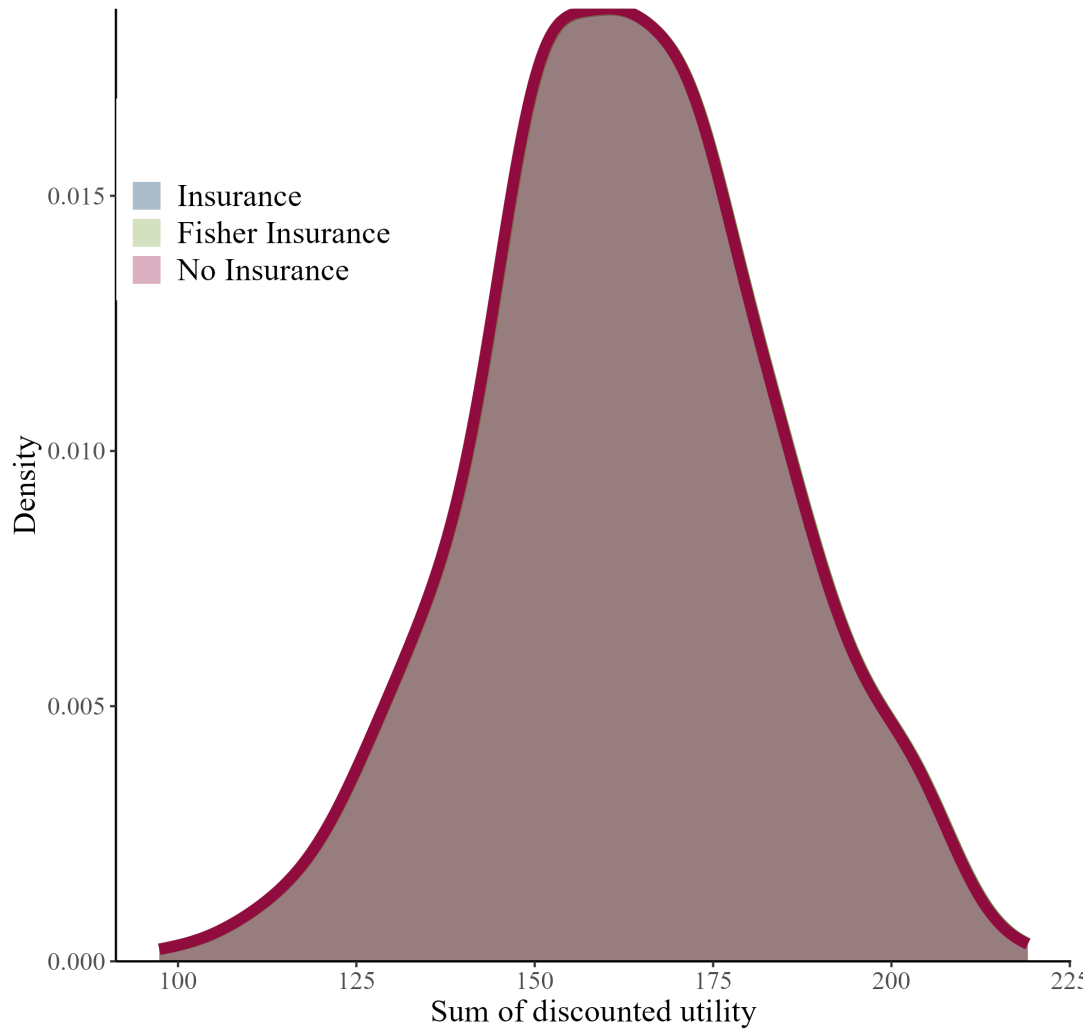


Figure 3.8: Distributions of total discounted fisher utility with insurance and manager updates harvest control rule (blue), only fisher insurance (green), and no insurance (red). Insurance premium is actuarially fair

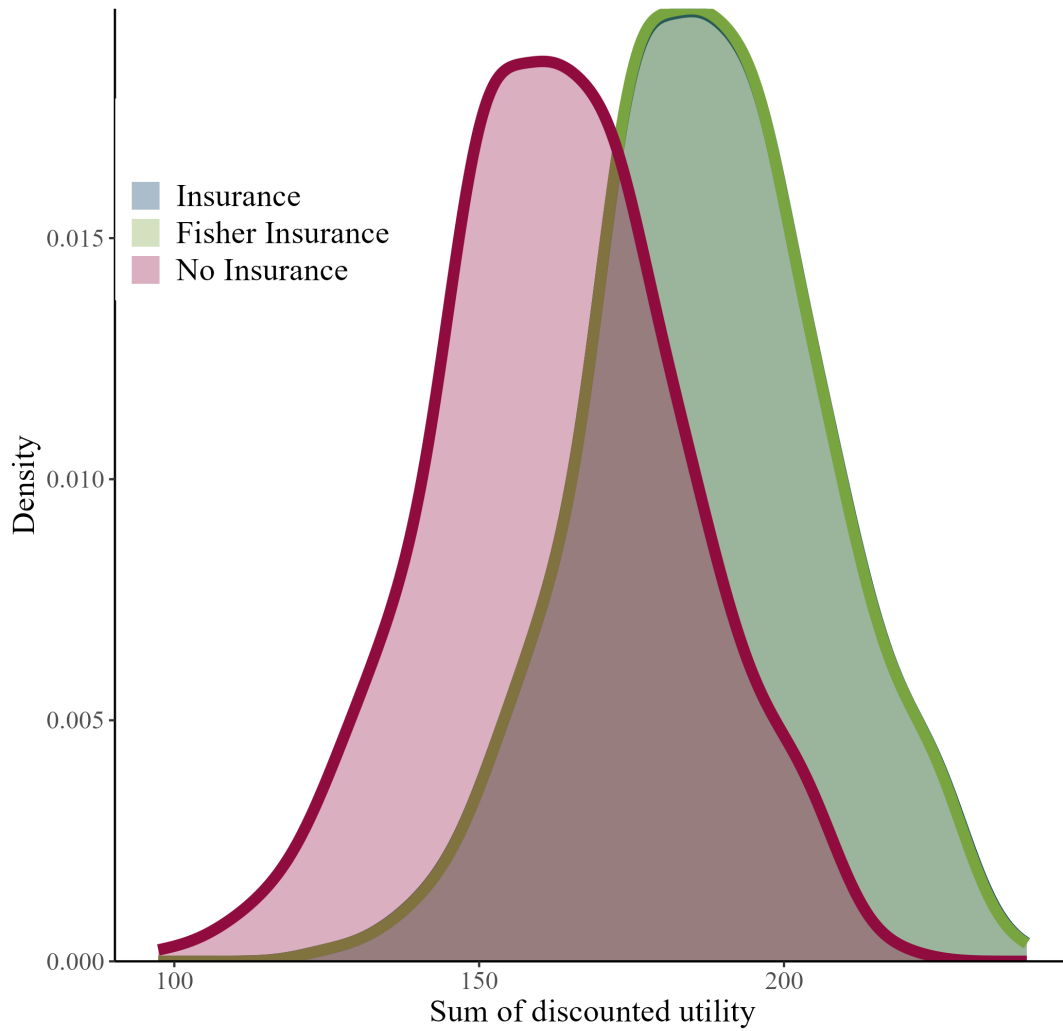


Figure 3.9: Distributions of total discounted fisher utility with insurance and manager updates harvest control rule (blue), only fisher insurance (green), and no insurance (red). Insurance premium is subsidized.

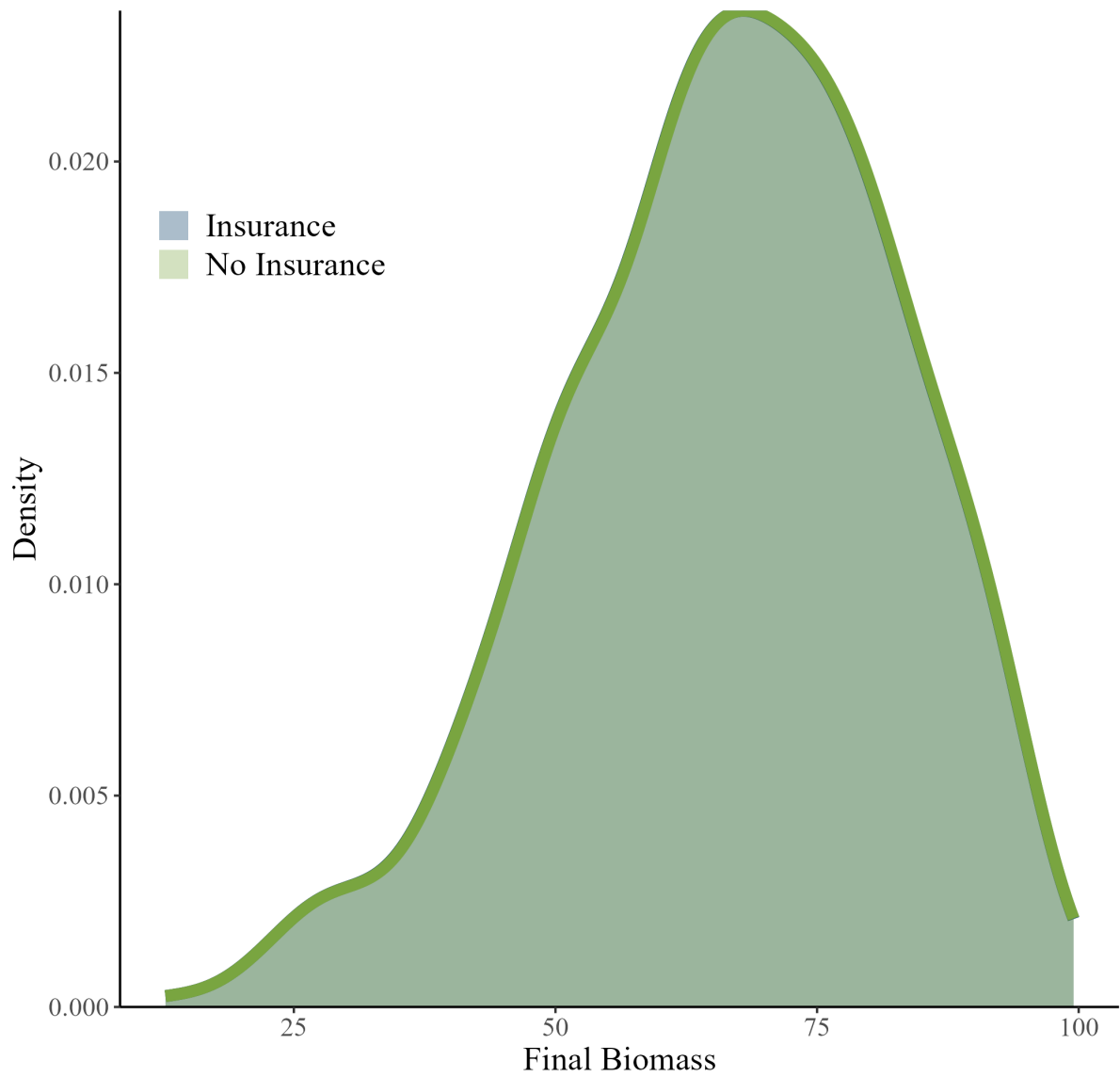


Figure 3.10: Distributions of final biomass after 30 years using the harvest control rule with insurance (blue) and without insurance (green) under the ex-ante information set.

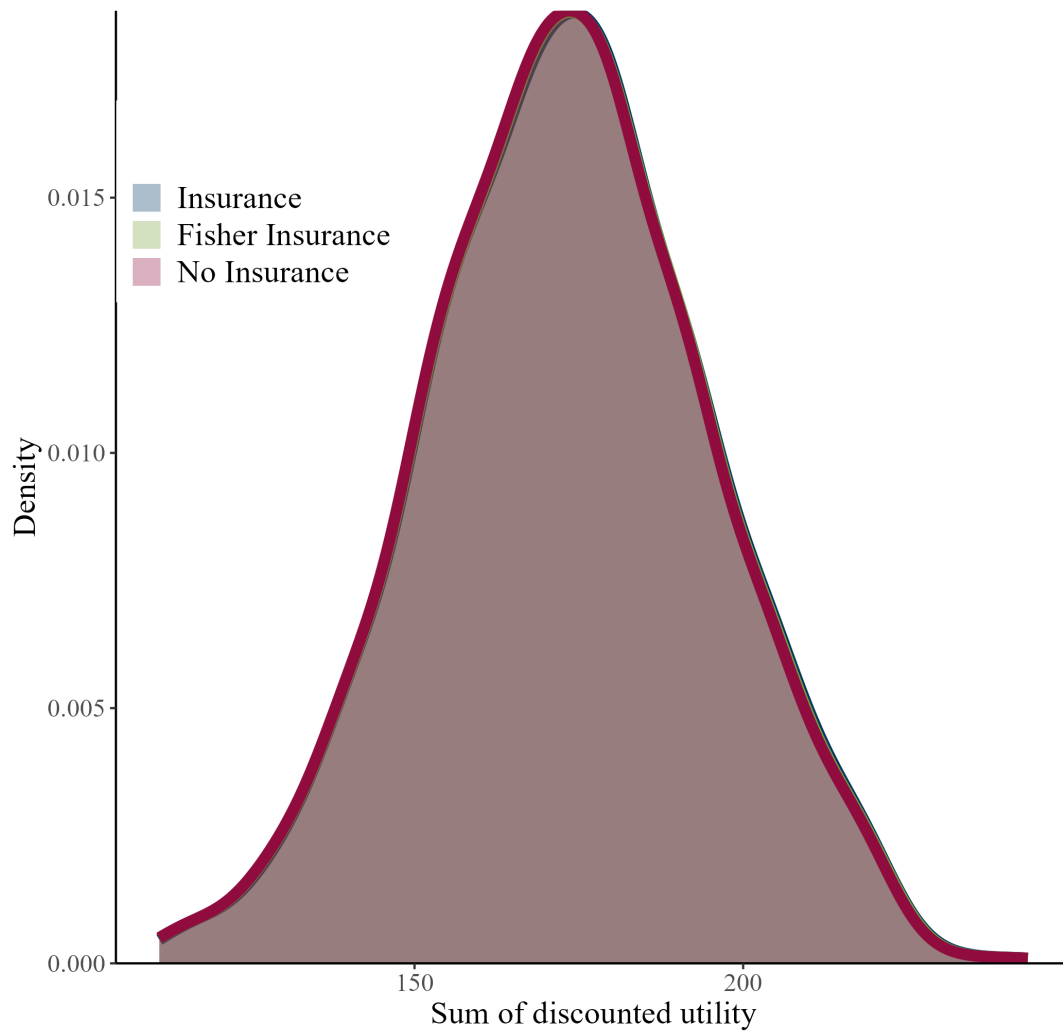


Figure 3.11: Distributions of total discounted fisher utility with insurance and manager updates harvest control rule (blue), only fisher insurance (green), and no insurance (red) under the ex-post information set. Insurance premium is actuarially fair.

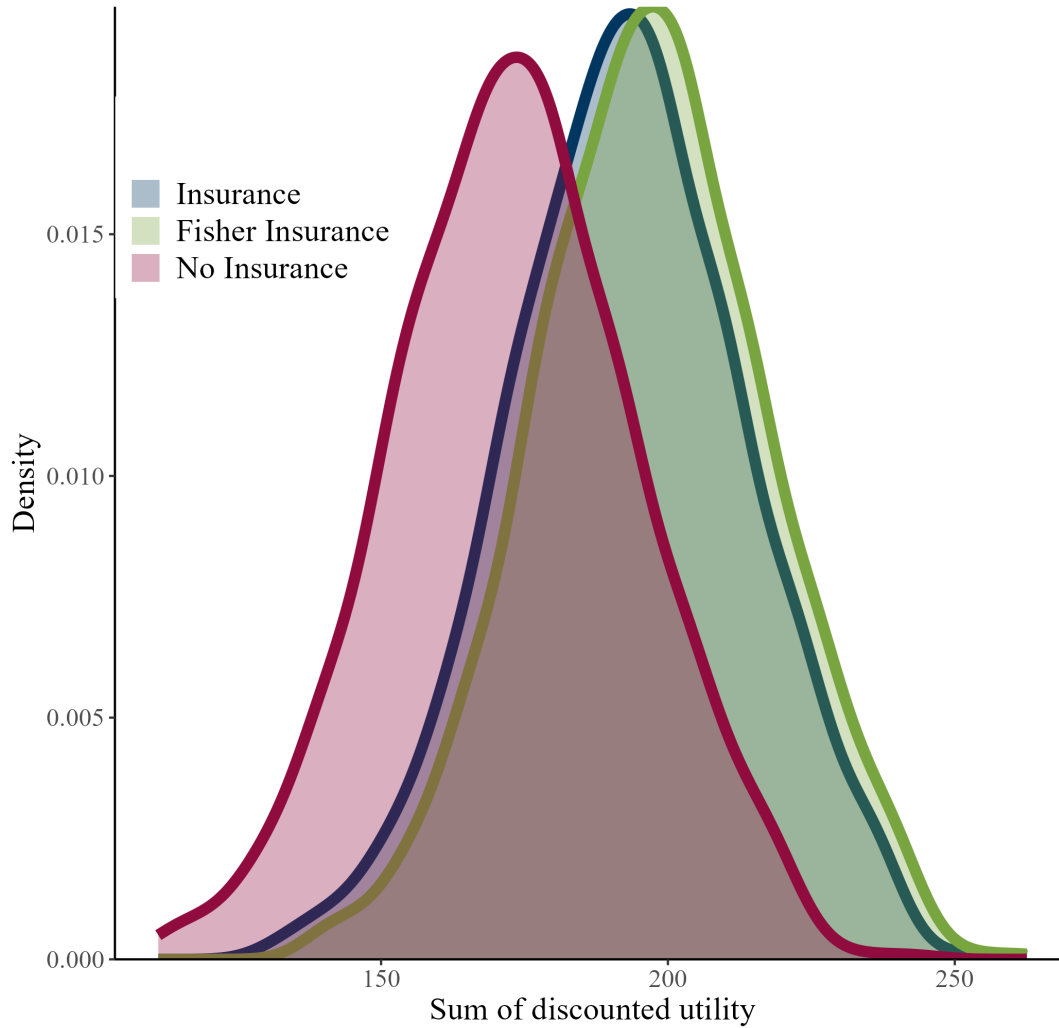


Figure 3.12: Distributions of total discounted fisher utility with insurance and manager updates harvest control rule (blue), only fisher insurance (green), and no insurance (red) under the ex-post information set. Insurance premium is subsidized.

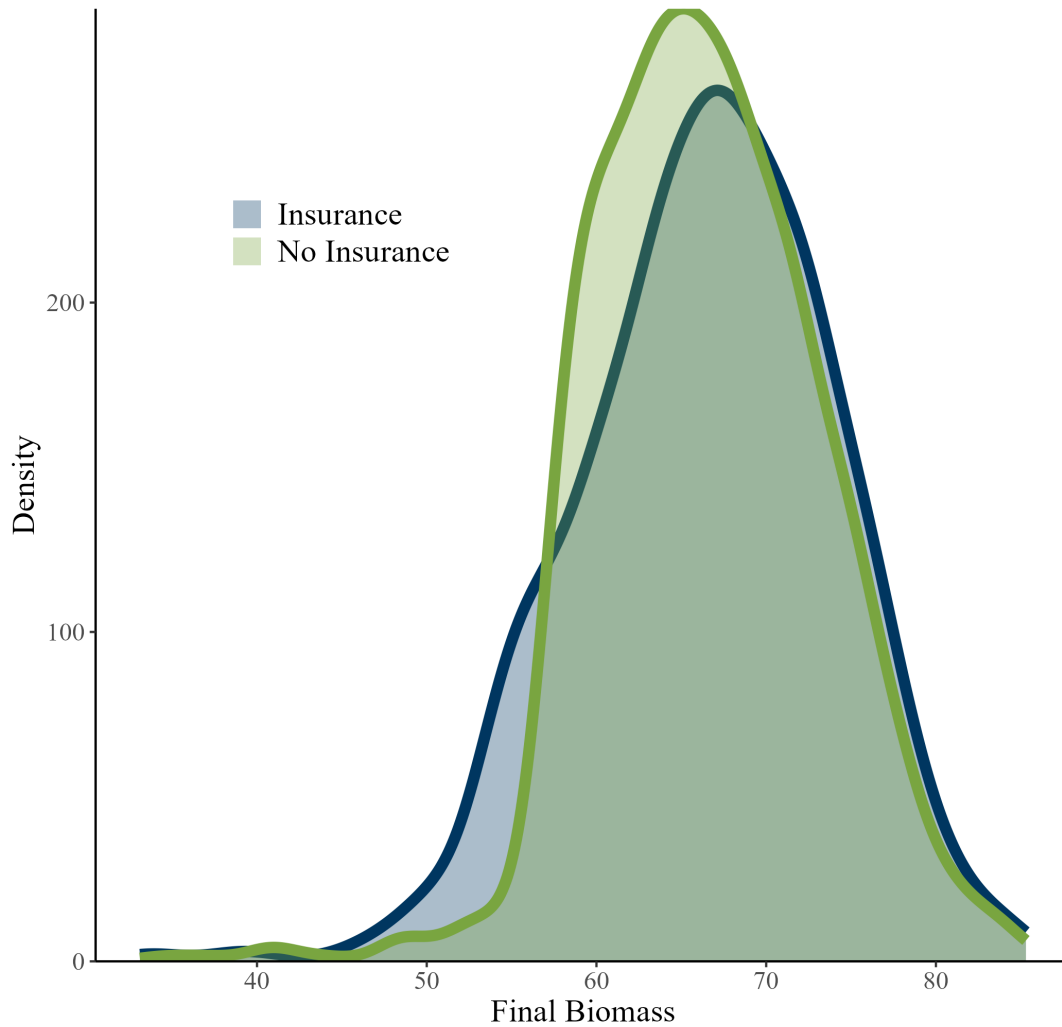


Figure 3.13: Distributions of total discounted fisher utility with insurance and manager updates harvest control rule (blue), only fisher insurance (green), and no insurance (red) under the ex-post information set. Insurance premium is actuarially fair.

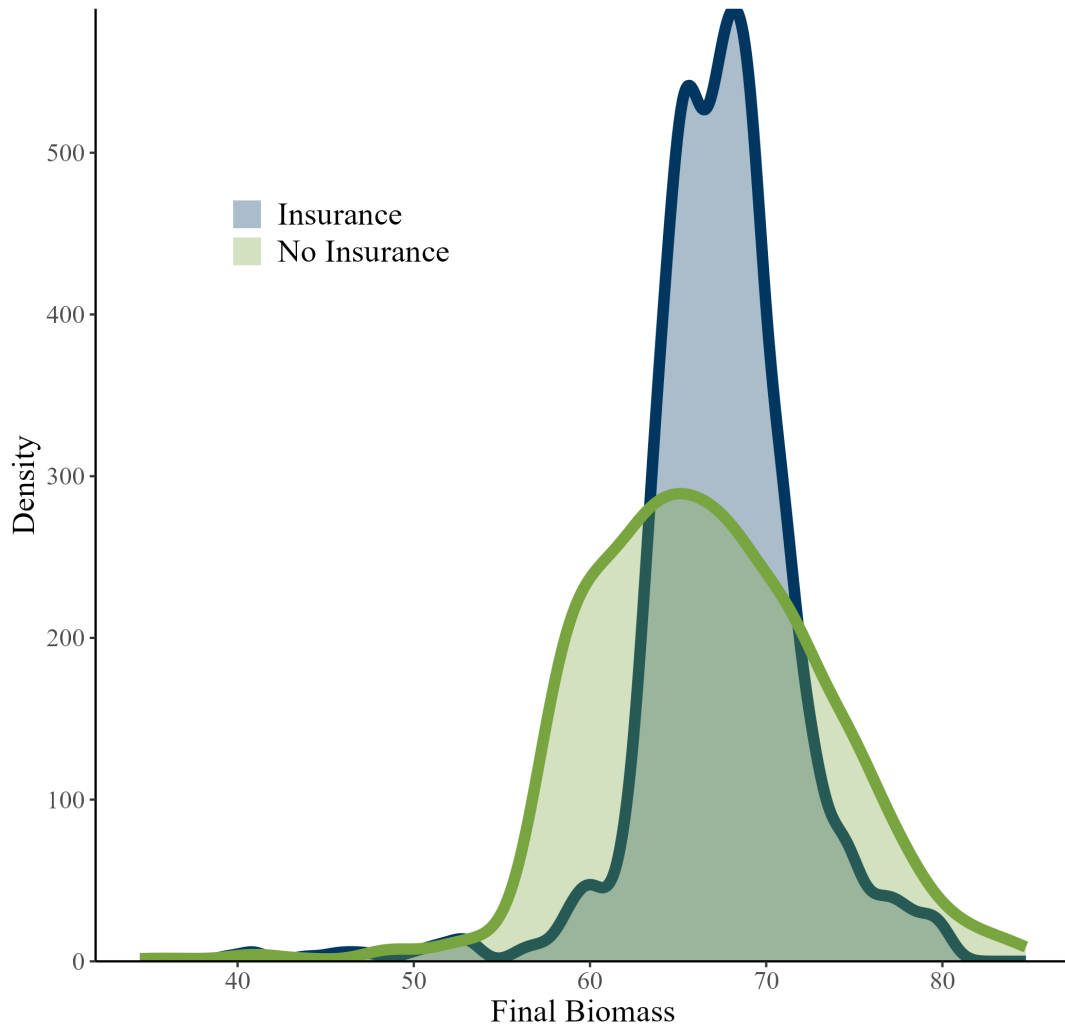


Figure 3.14: Distributions of total discounted fisher utility with insurance and manager updates harvest control rule (blue), only fisher insurance (green), and no insurance (red) under the ex-post information set. Insurance premium is subsidized

Appendix A

Chapter 1 Appendix

A.1 Section Title

A.1.1 Proof of Lemma 1.2.1

Lemma 2.1 *Index insurance contracts built on θ will always lead to higher expected marginal profits in the good state*

$$\frac{\mathbb{E}[\partial\pi|\theta < \bar{\theta}]}{\partial x} - \frac{\mathbb{E}[\partial\pi|\theta > \bar{\theta}]}{\partial x} < 0$$

Proof: With standard fishery production, $\pi = f(x)(\hat{\beta} + \theta) - c(x)$, the first order conditions lead to optimal input choices that are equal across states of the world. The choice of inputs occurs before the realization of the stochastic shock. Therefore $f(x^*)$, and $c(x^*)$ are equal across states. Where x^* denotes the optimal input choice.

$$\begin{aligned}
& \frac{\partial \mathbb{E}[\pi | \theta < \bar{\theta}]}{\partial x^*} - \frac{\partial \mathbb{E}[\pi | \theta > \bar{\theta}]}{\partial x^*} = \\
& \quad \cancel{f_{x^*}(x^*)\hat{B}} + \mathbb{E}[\theta f_x(x^*) | \theta < \bar{\theta}] - \cancel{c_{x^*}(x^*)} \\
& \quad - \cancel{f_{x^*}(x^*)\hat{B}} - \mathbb{E}[\theta f_x(x^*) | \theta > \bar{\theta}] + \cancel{c_{x^*}(x^*)} \\
& = \mathbb{E}[\theta f_x(x^*) | \theta < \bar{\theta}] - \mathbb{E}[\theta f_x(x^*) | \theta > \bar{\theta}]
\end{aligned} \tag{A.1}$$

With risky production profits are $\pi = \omega h(x) + f(x)(\hat{\beta} + \theta) - c(x)$. Independent shocks lead $\mathbb{E}[\omega | \theta \leq \bar{\theta}] = 0$.

$$\begin{aligned}
& \frac{\partial \mathbb{E}[\pi | \theta < \bar{\theta}]}{\partial x^*} - \frac{\partial \mathbb{E}[\pi | \theta > \bar{\theta}]}{\partial x^*} = \mathbb{E}[\theta f_x(x^*) | \theta < \bar{\theta}] - \mathbb{E}[\theta f_x(x^*) | \theta > \bar{\theta}] \\
& \quad + \cancel{f_{x^*}(x^*)\hat{B}} - \cancel{c_{x^*}(x^*)} \\
& \quad + \cancel{\mathbb{E}[\omega h_{x^*}(x^*) | \theta < \bar{\theta}]} - \cancel{\mathbb{E}[\omega h_{x^*}(x^*) | \theta > \bar{\theta}]} \\
& = \mathbb{E}[\theta f_x(x^*) | \theta < \bar{\theta}] - \mathbb{E}[\theta f_x(x^*) | \theta > \bar{\theta}].
\end{aligned} \tag{A.2}$$

The concavity of $f(x)$ leads to $f_x(x) > 0$. Equation A.1 and Equation A.2 can then be signed to be negative so that marginal profit in the good state is always higher when insurance contracts are triggered on θ .

$$\frac{\partial \mathbb{E}[\pi | \theta < \bar{\theta}]}{\partial x^*} - \frac{\partial \mathbb{E}[\pi | \theta > \bar{\theta}]}{\partial x^*} = \overbrace{\mathbb{E}[\theta f_{x^*}(x^*) | \theta < \bar{\theta}] - \mathbb{E}[\theta f_{x^*}(x^*) | \theta > \bar{\theta}]}^{-}$$

■

A.1.2 Proof of Lemma 1.3.1

Lemma 3.1 *Expected marginal profit is higher in bad states for risk decreasing inputs when contracts are built on extraction risk ω*

$$\frac{\mathbb{E}[\partial\pi|\omega < \bar{\omega}]}{\partial x} - \frac{\mathbb{E}[\partial\pi|\omega > \bar{\omega}]}{\partial x} > 0 \text{ if } h_x(x) < 0$$

Otherwise, risk increasing inputs lead to higher expected marginal profit in the good states.

$$\frac{\mathbb{E}[\partial\pi|\omega < \bar{\omega}]}{\partial x} - \frac{\mathbb{E}[\partial\pi|\omega > \bar{\omega}]}{\partial x} < 0 \text{ if } h_x(x) > 0$$

Proof:

By the first order conditions, there exist optimal values of any individual input x that must be chosen before the realization of the states of the world. Therefore $h(x^*)$, $f(x^*)$, and $c(x^*)$ are equal across states. Where x^* denotes the optimal input choice.

Marginal utility in both states of the world is controlled by risk effects and the sign of the random variables. Given θ is independent of ω , the expected value of $\mathbb{E}[\theta|\omega \leq \bar{\omega}] = 0$. The difference in expected marginal profit across insurance states is defined as:

$$\begin{aligned} \frac{\partial \mathbb{E}[\pi | \omega < \bar{\omega}]}{\partial x^*} - \frac{\partial \mathbb{E}[\pi | \omega > \bar{\omega}]}{\partial x^*} &= \mathbb{E}[\omega h_{x^*}(x^*) | \omega < \bar{\omega}] - \mathbb{E}[\omega h_{x^*}(x^*) | \omega > \bar{\omega}] \\ &\quad + \cancel{f_{x^*}(x^*)\hat{B}} - \cancel{c_{x^*}(x^*)} \\ &\quad + \cancel{\mathbb{E}[\theta f_x(x^*) | \omega < \bar{\omega}]} - \cancel{\mathbb{E}[\theta f_x(x^*) | \omega > \bar{\omega}]} \\ &= \mathbb{E}[\omega h_{x^*}(x^*) | \omega < \bar{\omega}] - \mathbb{E}[\omega h_{x^*}(x^*) | \omega > \bar{\omega}]. \end{aligned} \tag{A.3}$$

If an input is risk decreasing then $h_x(x) < 0$. Then Equation A.3 is positive and marginal profit in the bad state is greater than the marginal profit in the good state. Adding more of a risk reducing input reduces the negative impact in the bad state relative to the good state.

$$\frac{\partial \mathbb{E}[\pi|\omega < \bar{\omega}]}{\partial x^*} - \frac{\partial \mathbb{E}[\pi|\omega > \bar{\omega}]}{\partial x^*} = \overbrace{\mathbb{E}[\omega h_{x^*}(x^*)|\omega < \bar{\omega}] - \mathbb{E}[\omega h_{x^*}(x^*)|\omega > \bar{\omega}]}^{+}$$

Repeating the same steps for risk increasing inputs $h_x(x) > 0$ shows that marginal profit in the bad state is less than marginal profit in the good state.

$$\frac{\partial \mathbb{E}[\pi|\omega < \bar{\omega}]}{\partial x^*} - \frac{\partial \mathbb{E}[\pi|\omega > \bar{\omega}]}{\partial x^*} = \overbrace{\mathbb{E}[\omega h_{x^*}(x^*)|\omega < \bar{\omega}] - \mathbb{E}[\omega h_{x^*}(x^*)|\omega > \bar{\omega}]}^{-}$$

■

A.1.3 Proof of Proposition 1.4.1

Proposition 4.1 *In fisheries with two inputs, index insurance specified with contracts on ω will increase (decrease) the optimal use of a specific input if the input's risk effects are increasing (decreasing) when the following sufficient condition is true:*

$\frac{\partial^2 U}{\partial x_a \partial x_b} > 0$ when both inputs share the same risk effects, and $\frac{\partial^2 U}{\partial x_a \partial x_b} < 0$ when inputs have opposite risk effects.

Otherwise, index insurance will have ambiguous effects on optimal input choice.

Proof: We use the same insurance design from Section 1.3. Fishers now maximize expected utility by selecting two inputs. Contracts are built on ω .

$$U \equiv \max_{x_a, x_b} \mathbb{E}[U] = \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\bar{\omega}} j(\omega, \theta) u(\pi(X, \hat{B}, \theta, \omega) + (1 - J(\bar{\omega}))\gamma) d\omega + \int_{\bar{\omega}}^{\infty} j(\omega, \theta) u(\pi(X, \hat{B}, \theta, \omega) - J(\bar{\omega})\gamma) d\omega \right] d\theta \quad (\text{A.4})$$

Taking the first order conditions yields:

$$\begin{aligned}
\frac{\partial U}{\partial x_a} = & \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\bar{\omega}} j(\omega, \theta) u_{x_a} \left(\pi(X, \hat{B}, \theta, \omega) + (1 - J(\bar{\omega}))\gamma \right) \right. \\
& \times \frac{\partial \pi}{\partial x_a}(X, \hat{B}, \theta, \omega) d\omega \\
& + \int_{\bar{\omega}}^{\infty} j(\omega, \theta) u_{x_a} \left(\pi(X, \hat{B}, \theta, \omega) - J(\bar{\omega})\gamma \right) \\
& \times \frac{\partial \pi}{\partial x_a}(X, \hat{B}, \theta, \omega) d\omega \left. \right] d\theta = 0,
\end{aligned} \tag{A.5}$$

$$\begin{aligned}
\frac{\partial U}{\partial x_b} = & \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\bar{\omega}} j(\omega, \theta) u_{x_b} \left(\pi(X, \hat{B}, \theta, \omega) + (1 - J(\bar{\omega}))\gamma \right) \right. \\
& \times \frac{\partial \pi}{\partial x_b}(X, \hat{B}, \theta, \omega) d\omega \\
& + \int_{\bar{\omega}}^{\infty} j(\omega, \theta) u_{x_b} \left(\pi(X, \hat{B}, \theta, \omega) - J(\bar{\omega})\gamma \right) \\
& \times \frac{\partial \pi}{\partial x_b}(X, \hat{B}, \theta, \omega) d\omega \left. \right] d\theta = 0.
\end{aligned}$$

Assuming the first order condition is satisfied, we can use the implicit function theorem (IFT) to look at the impact of a change in the exogenous insurance contract. Applying IFT yields a system of equations that determine the impact of insurance on each optimal input:

$$\begin{aligned}
\frac{\partial x_a}{\partial \gamma} &= \frac{-1}{Det} \left[\frac{\partial U}{\partial x_b \partial x_b} \frac{\partial U}{\partial x_a \partial \gamma} - \frac{\partial U}{\partial x_a \partial x_b} \frac{\partial U}{\partial x_b \partial \gamma} \right] \\
\frac{\partial x_b}{\partial \gamma} &= \frac{-1}{Det} \left[\frac{-\partial U}{\partial x_b \partial x_a} \frac{\partial U}{\partial x_a \partial \gamma} + \frac{\partial U}{\partial x_a \partial x_a} \frac{\partial U}{\partial x_b \partial \gamma} \right]
\end{aligned} \tag{A.6}$$

Because the determinant (DET) will always be positive by the second-order condition, we can focus on the interior of the brackets. If positive, then insurance will lower use of that specific input and vice versa. The partial derivatives in Equation A.6 are complex. Their complete derivations are included in Section A.1.4.

Lemma 1.3.1 allows us to sign the partial equations Equation A.12 and Equation A.13

for any risk effect on either input. Concave utility by definition leads to $u'' < 0$. For simplicity, we will only focus on $\frac{\partial^2 U}{\partial x_a \partial \gamma}$, but all applies equally to $\frac{\partial^2 U}{\partial x_b \partial \gamma}$. Insurance payouts equalize profits between different states. If insurance completely covers all loss and x_a is risk increasing, then $\frac{\partial^2 U}{\partial x_a \partial \gamma}$ is positive.

$$\begin{aligned} \frac{\partial^2 U}{\partial x_a \partial \gamma} &= \int_{-\infty}^{\infty} \overbrace{j_{\theta}(\theta) J(\bar{\theta}) (1 - J(\bar{\theta})) u''(\theta, \cdot)}^{-} \\ &\quad \left[\underbrace{\int_{-\infty}^{\bar{\omega}} j_{\omega}(\omega) \frac{\partial \pi}{\partial x_a} d\omega - \int_{\bar{\theta}}^{\infty} j_{\omega}(\omega) \frac{\partial \pi}{\partial x_a} d\omega}_{-} \right] d\theta \quad (\text{A.7}) \\ &> 0 \end{aligned}$$

Suppose both inputs are risk increasing so $\frac{\partial^2 U}{\partial x_a \partial \gamma}$ and $\frac{\partial^2 U}{\partial x_b \partial \gamma}$ are positive. The only way for Equation A.6 to be unambiguously positive is for $\frac{\partial^2 U}{\partial x_a \partial x_b}$ and $\frac{\partial^2 U}{\partial x_b \partial x_a}$ to be positive.

$$\begin{aligned} \frac{\partial x_a}{\partial \gamma} &= \frac{\overbrace{-1}^{-}}{Det} \left[\overbrace{\frac{\partial^2 U}{\partial x_b \partial x_b} \frac{\partial^2 U}{\partial x_a \partial \gamma} - \frac{\partial^2 U}{\partial x_a \partial x_b} \frac{\partial^2 U}{\partial x_b \partial \gamma}}^{-} \right] > 0 \\ \frac{\partial x_b}{\partial \gamma} &= \frac{\overbrace{-1}^{-}}{Det} \left[\overbrace{\frac{-\partial^2 U}{\partial x_b \partial x_a} \frac{\partial^2 U}{\partial x_a \partial \gamma} + \frac{\partial^2 U}{\partial x_a \partial x_a} \frac{\partial^2 U}{\partial x_b \partial \gamma}}^{-} \right] > 0 \end{aligned}$$

Both risk increasing inputs will be raised with index insurance. Repeating the same steps above with risk decreasing inputs shows both inputs unambiguously decrease with index insurance.

Now suppose inputs have mixed risk effects. For simplicity, x_a will be risk increas-

ing and x_b will be risk decreasing. The results will hold for the opposite case. By Lemma 1.3.1, $\frac{\partial^2 U}{\partial x_a \partial \gamma}$ is positive, while $\frac{\partial^2 U}{\partial x_b \partial \gamma}$ is negative. Equation A.6 will be unambiguously positive if $\frac{\partial^2 U}{\partial x_a \partial x_b}$ and $\frac{\partial^2 U}{\partial x_b \partial x_a}$ are negative.

$$\begin{aligned} \frac{\partial x_a}{\partial \gamma} &= \frac{\overbrace{-1}^{-}}{Det} \left[\overbrace{\frac{\partial^2 U}{\partial x_b \partial x_b} \frac{\partial^2 U}{\partial x_a \partial \gamma} - \frac{\partial^2 U}{\partial x_a \partial x_b} \frac{\partial^2 U}{\partial x_b \partial \gamma}}^{-} \right] > 0 \\ \frac{\partial x_b}{\partial \gamma} &= \frac{\overbrace{-1}^{-}}{Det} \left[\overbrace{\frac{-\partial^2 U}{\partial x_b \partial x_a} \frac{\partial^2 U}{\partial x_a \partial \gamma} + \frac{\partial^2 U}{\partial x_a \partial x_a} \frac{\partial^2 U}{\partial x_b \partial \gamma}}^{+} \right] < 0 \end{aligned}$$

The risk increasing input will be raised with index insurance, while the risk decreasing input will be lowered.

If these conditions do not hold, then it is impossible to determine which additive element outweighs the other, and the insurance effects on optimal input use will be ambiguous regardless of the underlying risk effects of an input. ■

A.1.4 Partial derivatives

Partial derivatives used to sign Equation A.6 are shown below. For brevity, $\pi(X, \hat{B}, \omega, \theta)$ is reduced to π .

$$\begin{aligned}
\frac{\partial^2 U}{\partial x_a \partial x_a} = & \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\bar{\omega}} j(\omega, \theta) \left\{ u''(\pi + (1 - J(\bar{\omega}))\gamma) \frac{\partial \pi}{\partial x_a} \right. \right. \\
& + u'(\pi + (1 - J(\bar{\omega}))\gamma) \frac{\partial^2 \pi}{\partial x_a^2} \left. \right\} d\omega \\
& + \int_{\bar{\omega}}^{\infty} j(\omega, \theta) \left\{ u''(\pi - J(\bar{\omega})\gamma) \frac{\partial \pi}{\partial x_a} \right. \\
& + u'(\pi - J(\bar{\omega})\gamma) \frac{\partial^2 \pi}{\partial x_a^2} \left. \right\} d\omega \left. \right] d\theta.
\end{aligned} \tag{A.8}$$

$$\begin{aligned}
\frac{\partial^2 U}{\partial x_b \partial x_b} = & \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\bar{\omega}} j(\omega, \theta) \left\{ u''(\pi + (1 - J(\bar{\omega}))\gamma) \frac{\partial \pi}{\partial x_b} \right. \right. \\
& + u'(\pi + (1 - J(\bar{\omega}))\gamma) \frac{\partial^2 \pi}{\partial x_b^2} \left. \right\} d\omega \\
& + \int_{\bar{\omega}}^{\infty} j(\omega, \theta) \left\{ u''(\pi - J(\bar{\omega})\gamma) \frac{\partial \pi}{\partial x_b} \right. \\
& + u'(\pi - J(\bar{\omega})\gamma) \frac{\partial^2 \pi}{\partial x_b^2} \left. \right\} d\omega \left. \right] d\theta.
\end{aligned} \tag{A.9}$$

$$\begin{aligned}
\frac{\partial^2 U}{\partial x_a \partial x_b} = & \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\bar{\omega}} j(\omega, \theta) \left\{ u''(\pi + (1 - J(\bar{\omega}))\gamma) \frac{\partial \pi}{\partial x_a} \frac{\partial \pi}{\partial x_b} \right. \right. \\
& + u'(\pi + (1 - J(\bar{\omega}))\gamma) \frac{\partial^2 \pi}{\partial x_a \partial x_b} \left. \right\} d\omega \\
& + \int_{\bar{\omega}}^{\infty} j(\omega, \theta) \left\{ u''(\pi - J(\bar{\omega})\gamma) \frac{\partial \pi}{\partial x_a} \frac{\partial \pi}{\partial x_b} \right. \\
& + u'(\pi - J(\bar{\omega})\gamma) \frac{\partial^2 \pi}{\partial x_a \partial x_b} \left. \right\} d\omega \left. \right] d\theta.
\end{aligned} \tag{A.10}$$

$$\begin{aligned}
\frac{\partial^2 U}{\partial x_b \partial x_a} = & \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\bar{\omega}} j(\omega, \theta) \left\{ u''(\pi + (1 - J(\bar{\omega}))\gamma) \frac{\partial \pi}{\partial x_a} \frac{\partial \pi}{\partial x_b} \right. \right. \\
& + u'(\pi + (1 - J(\bar{\omega}))\gamma) \frac{\partial^2 \pi}{\partial x_b \partial x_a} \left. \right\} d\omega \\
& + \int_{\bar{\omega}}^{\infty} j(\omega, \theta) \left\{ u''(\pi - J(\bar{\omega})\gamma) \frac{\partial \pi}{\partial x_a} \frac{\partial \pi}{\partial x_b} \right. \\
& + u'(\pi - J(\bar{\omega})\gamma) \frac{\partial^2 \pi}{\partial x_b \partial x_a} \left. \right\} d\omega \left. \right] d\theta.
\end{aligned} \tag{A.11}$$

$$\begin{aligned}
\frac{\partial^2 U}{\partial x_a \partial \gamma} = & \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\bar{\omega}} j(\omega, \theta) u''(\pi + (1 - J(\bar{\omega}))\gamma) \frac{\partial \pi}{\partial x_a} (1 - J(\bar{\omega})) d\omega \right. \\
& \left. \int_{\bar{\omega}}^{\infty} j(\omega, \theta) u''(\pi - J(\bar{\omega})\gamma) \frac{\partial \pi}{\partial x_a} (-J(\bar{\omega})) d\omega \right] d\theta
\end{aligned} \tag{A.12}$$

$$\begin{aligned}
\frac{\partial^2 U}{\partial x_b \partial \gamma} = & \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\bar{\omega}} j(\omega, \theta) u''(\pi + (1 - J(\bar{\omega}))\gamma) \frac{\partial \pi}{\partial x_b} (1 - J(\bar{\omega})) d\omega \right. \\
& \left. \int_{\bar{\omega}}^{\infty} j(\omega, \theta) u''(\pi - J(\bar{\omega})\gamma) \frac{\partial \pi}{\partial x_b} (-J(\bar{\omega})) d\omega \right] d\theta
\end{aligned} \tag{A.13}$$

A.1.5 Single Input Simulations

This section examines a simple one input case to demonstrate how an endogenous choice of insurance coverage does not change the direction of inputs, the effects of input productivity on the magnitude of change, and a comparative static analysis of other inputs beyond the risk effects. We use the structural form where $f(x) = x^\alpha$ and $h(x) = x^\beta$ to most easily integrate risk increasing or decreasing effects in $h(x)$. Under these functional forms, profit becomes:

$$\pi = x^\alpha (\hat{\beta} + \theta) + \omega x^\beta - cx^2 \tag{A.14}$$

Mean production $f(x)$ is concave so that $0 < \alpha < 1$. Extraction risk effects on the input can either be risk increasing or decreasing with $\beta \lessgtr 0$. We apply convex

costs, $c(x) = cx^2$, for smoother convergence in the maximization procedure. Stock and extraction shocks are normally distributed with $\theta \sim N(0, \sigma_\theta)$ and $\omega \sim N(0, \sigma_\omega)$.

Fishers will choose inputs x to maximize expected utility with an exogenous insurance contract. Constant Absolute Risk Aversion (CARA) utility is used so that utility remains defined if net profits are negative. Under this contract specification, the utility maximization problem in 1.11 becomes:

$$U \equiv \max_x \mathbb{E}[u] = \mathbb{E}[(1 - \exp(-a(\pi(x, \hat{\beta}, \theta, \omega) + \mathbb{I}(\gamma)))]$$

$$\mathbb{I}(\gamma) = \begin{cases} -\rho\gamma & \text{if } \omega \geq \bar{\omega} \\ (1 - \rho)\gamma & \text{if } \omega < \bar{\omega} \end{cases} \quad (\text{A.15})$$

We define γ as a percentage of mean optimal profit without insurance for interpretability. For example, $\gamma = 1$ would represent a payout equivalent to expected profit before insurance, and $\gamma = 0$ represents no insurance. Equation A.15 shows the insurance payoff function $I(\gamma)$ built on extraction risk with $\bar{\omega}$ as the trigger. A contract built on stock risk would instead use $\bar{\theta}$ and θ as the conditions in the payoff function.

We create a large parameter space to assess the sensitivity of optimal input choices to different model parameters. We vary the relative productivity of the input $\alpha \in \{0.25, 0.5, 0.75\}$, the extraction risk effect of the input $\beta \in \{-0.7, -0.5, -0.3, -0.1, 0.1, 0.3, 0.5, 0.7\}$, the risk aversion parameter $a \in \{1, 2, 3\}$, and both random variable variances $\sigma_\theta, \sigma_\omega \in \{0.1, 0.2, 0.3, 0.4\}$.

For any level of insurance payout γ , input use changes monotonically consistent with the conditions of Proposition 1.3.2 and Proposition 1.3.1 (Figure A.1). Fishers maximize utility at point B in the bottom right panel of Figure A.1. Point A shows the no insurance case. Any coverage between point A and B will improve utility. Limits on coverage could constrain fishers to this area, but the direction of input use remains constant.

Overinvestment in insurance, as shown by point C, could reduce utility as the premiums become excessive large. Input use continues to increase beyond optimal levels.

The monotonicity of input use in all cases suggests that the insurance level that maximizes utility will preserve the sign of input changes. Therefore, allowing fishers to choose the amount of insurance coverage will not affect the direction of input change, but it will affect the magnitude.

For example, the utility maximizing point for contracts protecting against extraction risks when inputs are risk decreasing would be further to left than contracts on stock risks in Figure A.1. Fishers would be better off with lower levels of insurance coverage. Allowing fishers to choose insurance coverage ensures that the choice of insurance is welfare improving and will not bias input choices with over or under investment of insurance. Simulations moving forward will allow fishers to choose both inputs and insurance coverage.

The maximization problem is updated to include two choice variables:

$$U \equiv \max_{x, \gamma} \mathbb{E}[u] = \mathbb{E}[(1 - \exp(-a(\pi(x, \hat{\beta}, \theta, \omega) + \mathbb{I}(\gamma)))]$$

$$\mathbb{I}(\gamma) = \begin{cases} -\rho\gamma & \text{if } \omega \geq \bar{\omega} \\ (1 - \rho)\gamma & \text{if } \omega < \bar{\omega} \end{cases} \quad (\text{A.16})$$

Furthermore, we run two groups of simulations: (i) one where the insurance contract indemnifies on ω , as in Equation A.15; and (ii) one where the index is constructed on θ .

The productivity of inputs strongly influences the magnitude of change in input use particularly for risk decreasing inputs. When inputs are relatively less productive (left panel, $\alpha = 0.25$), fishers are more willing to reduce the unproductive input in favor of the protection offered by insurance. They lose less in production while gaining more variance reduction by substituting with insurance. Fishers demonstrate smaller absolute changes

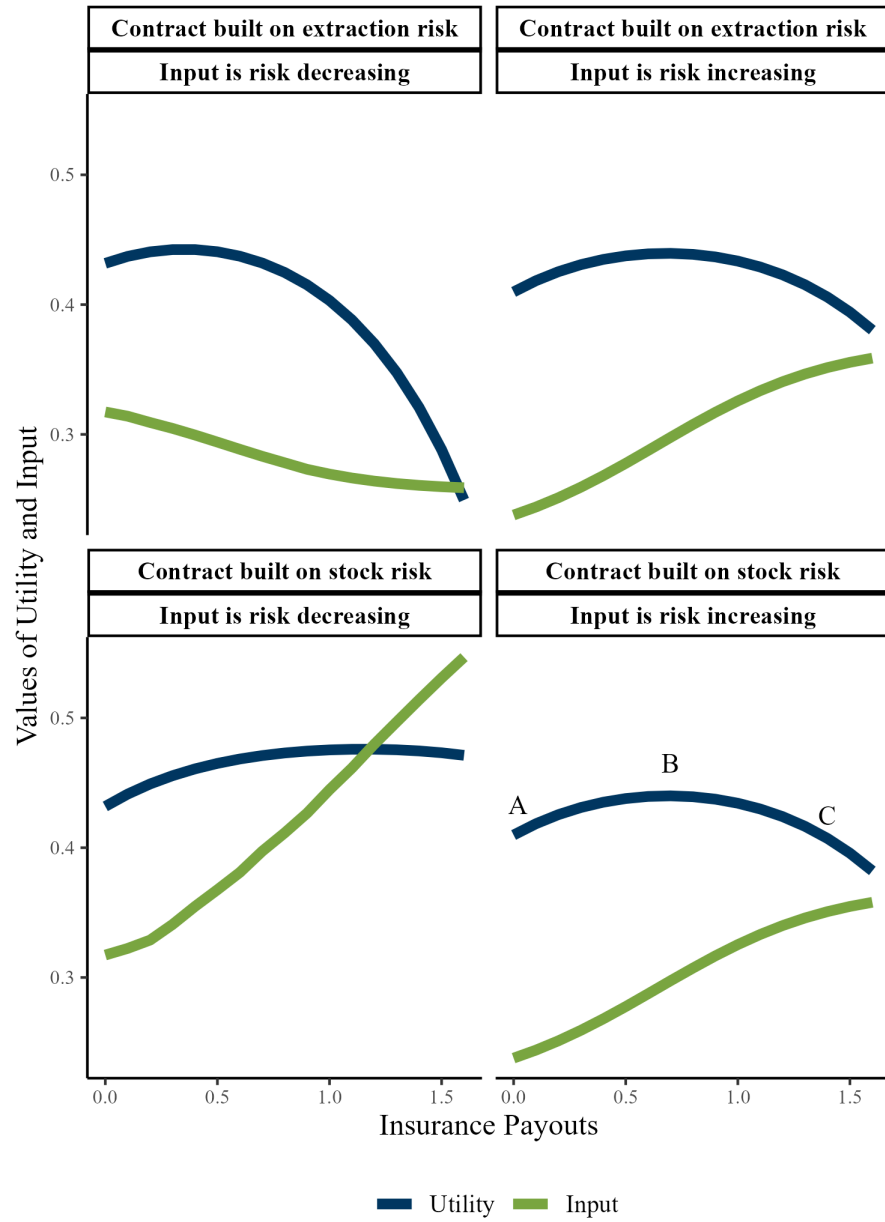


Figure A.1: Utility (blue lines) and optimal input use (green lines) with increasing levels of constant index insurance payouts. Inputs have high mean productivity ($\alpha = 0.75$), fishers are highly risk averse $a = 3$, and there is high variance in both shocks ($\sigma_w = 0.4$ and $\sigma_t = 0.4$).

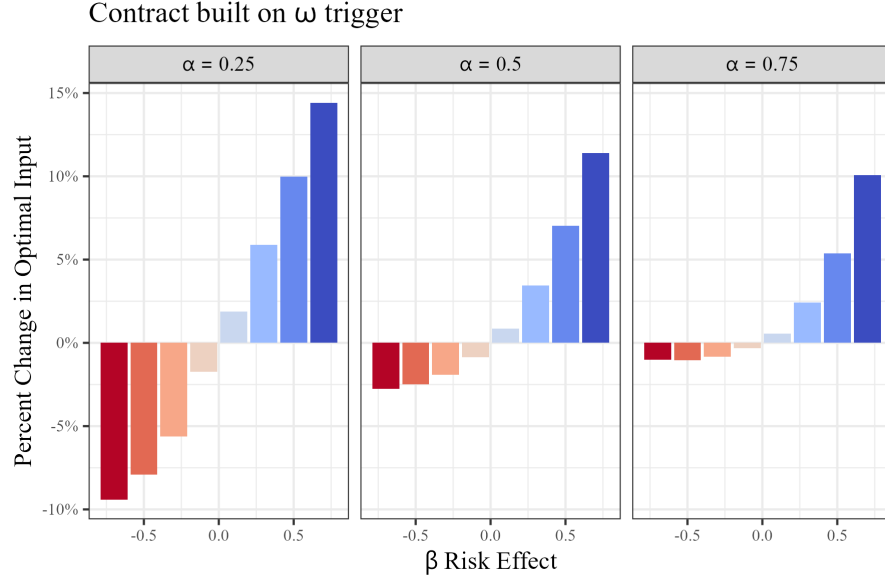


Figure A.2: Percentage change in optimal input with an index insurance contract using extraction risk, ω , as the index. Risk increasing inputs (blue bars) always increase input use, while risk decreasing inputs (red bars) always decrease input use. Each panel indicates the mean productivity (α) of the input.

in input use for risk decreasing inputs than risk increasing particularly at higher mean productivity levels in Figure A.2.

Index insurance will incentivize higher use of more productive inputs if contracts are indexed on θ (Figure A.3). The right most panel of Figure A.3 shows the highest effect where input changes could increase by 18% relative to no insurance. Extraction risk in $h(x)$ has little influence on changes in optimal input use when the contract is specified on stock risk. Across all levels of the risk effect, β , the magnitude of change remains relatively constant for a given productivity level.

Magnitude of input changes are sensitive to other parameters beyond just mean production elasticity (α). We quickly demonstrate some comparative statics of other important variables such as risk aversion (Panel A in Figure A.4), trigger thresholds (Panel B), variance of the extraction risk σ_ω (Panel C), and variance of the stock risk σ_θ (Panel D). In each panel, we show the results for the contracts specified on stock risk (θ) and

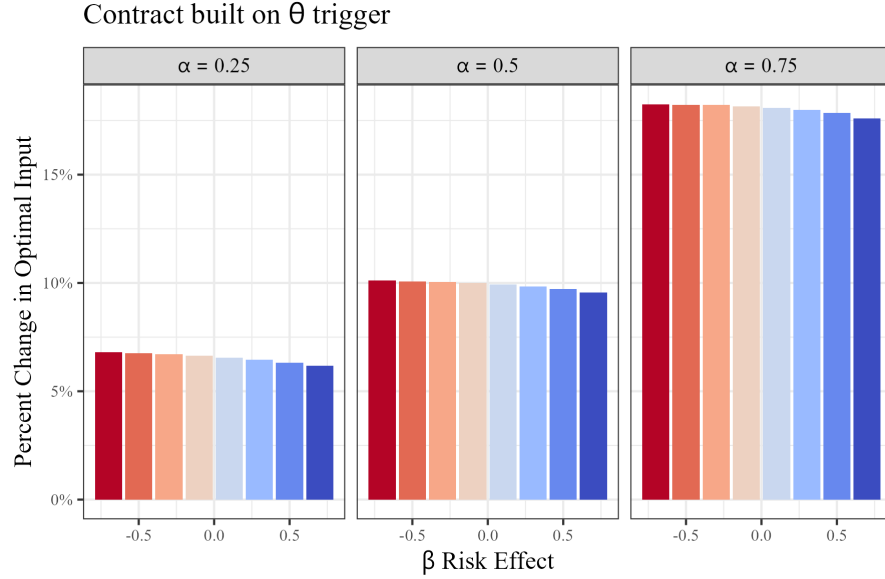


Figure A.3: Percentage change in optimal input with an index insurance contract using stock risk, θ , as the index. Risk increasing inputs (blue bars) and risk decreasing inputs (red bars) always increase input use. Each panel indicates the mean productivity (α) of the input.

extraction risk (ω). The x-axis of each panel is the extraction risk effect coefficient β , while the y-axis is the percent change in input use with index insurance compared to no insurance. Different colors represent the comparative statics of each new parameter. Across all panels, the new parameters affect only the magnitude of change. The direction of change continues to be determined by risk effects and contract specification.

More risk averse fishers respond more aggressively to insurance (Panel A in Figure A.4). Risk aversion implies more sensitivity towards risk. The protection from insurance has greater marginal value for more risk averse fishers. Therefore, they adjust their input use more significantly to take advantage of the risk mitigating qualities of insurance.

Different triggers also lead to different magnitudes of input change, but do not affect the sign changes. While necessary for applying Lemma 1.3.1 and Lemma 1.2.1 in the proofs, the results of Proposition 1.3.1 and Proposition 1.3.2 would appear to hold if

$\bar{\omega} \neq 0$ and $\bar{\theta} \neq 0$. Higher trigger levels protect against extreme or catastrophic shocks. However, those shocks occur much less frequently than those closer to the mean. Fishers are less incentivized to change their expected production levels in the event of rare events. Offering different insurance contracts does change the optimal choice of insurance in line with the results of Lichtenberg and Iglesias (2022).

Fisher input choice is much more responsive to insurance protection from more variable shocks (Panel C and D Figure A.4), but it depends on the insurance contract. Similar to risk aversion, the greater the shocks the greater the marginal value of insurance to mitigate those shocks. In more volatile environments, insurance provides significantly more income smoothing leading to similar incentives as the higher risk aversion example. Shocks the insurance does not protect against has little influence on fisher input decisions. If the insurance is designed to protect against one specific shock, it is unsurprising changes in the other independent shock does not affect fishers decisions.

A.1.6 Correlation Proofs

Lemma A.1.1 () *When shocks are perfectly correlated, expected marginal profit is always higher in the good state when an input, x , is risk increasing and ambiguous when x is risk decreasing. This hold regardless of the chosen index.*

$$\frac{\mathbb{E}[\partial\pi|\omega<\bar{\omega}]}{\partial x} - \frac{\mathbb{E}[\partial\pi|\omega>\bar{\omega}]}{\partial x} < 0 \text{ if } h_x(X) > 0$$

$$\text{And, } \frac{\mathbb{E}[\partial\pi|\omega<\bar{\omega}]}{\partial x} - \frac{\mathbb{E}[\partial\pi|\omega>\bar{\omega}]}{\partial x} \leq 0 \text{ if } h_{x_m}(X) < 0.$$

Proof: Perfect correlation between two random variables centered at 0 imply that whenever one variable is negative, so too is the other. Due to this, we focus only on ω as the index. The proof follows identically if replaced by an index on θ .

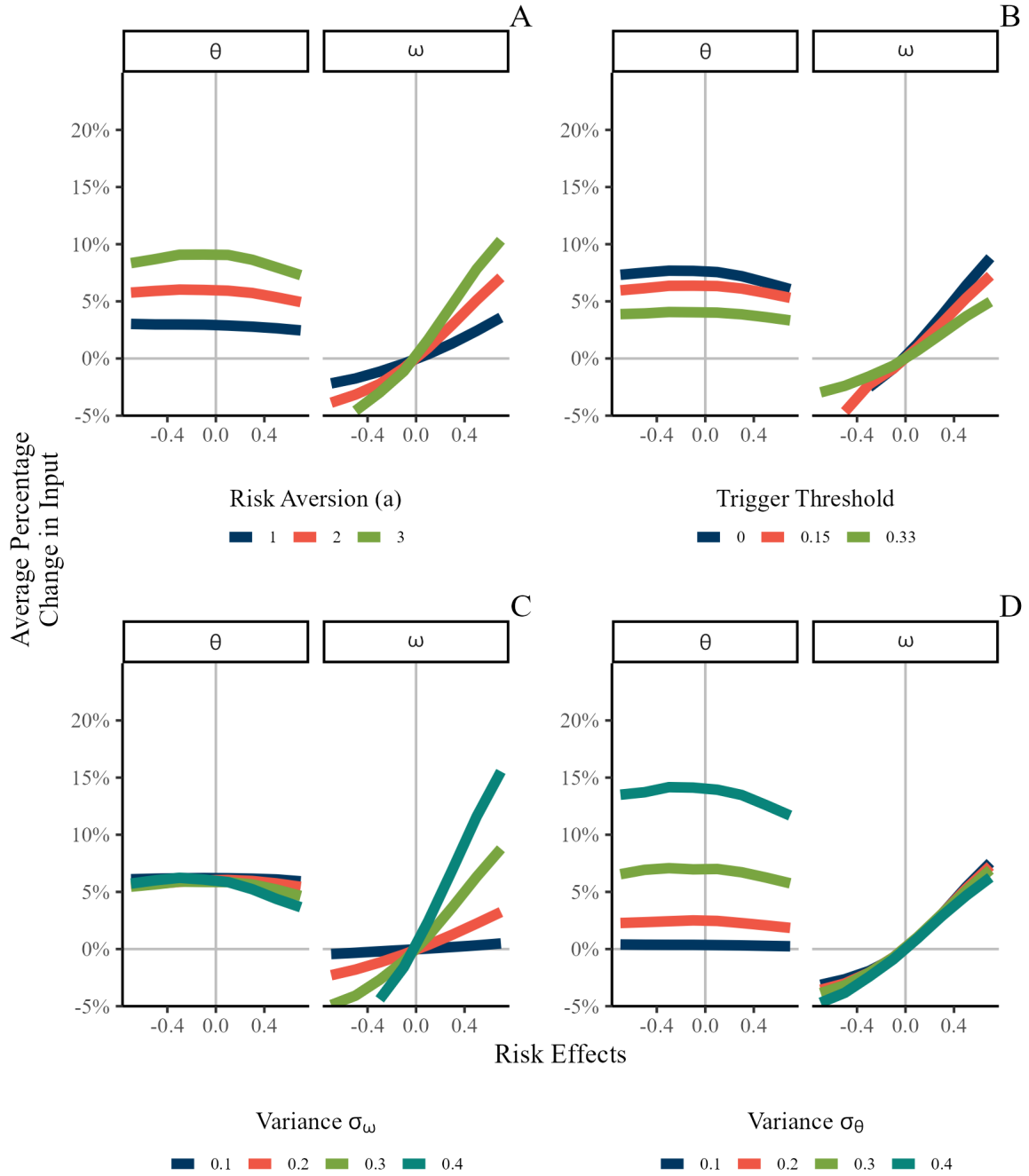


Figure A.4: Risk Aversion (A), trigger threshold (B), stock variance σ_ω (C), and extraction variance σ_θ (D) all influence the magnitude of change in input use. Mean production elasticity is set to 0.5. Average percent change in input (y-axis) is summarized across all other parameter combinations for each risk effect value of β . Contracts built on extraction risk are in the subpanels with ω , while contracts built on stock risk are indicated by the θ subpanel.

$$\begin{aligned}
& \frac{\partial \mathbb{E}[\pi|\omega < \bar{\omega}]}{\partial x} - \frac{\partial \mathbb{E}[\pi|\omega > \bar{\omega}]}{\partial x} = \\
& \quad \cancel{f_x(x)}\hat{B} + \mathbb{E}[\theta f_x(x)|\omega < \bar{\omega}] + \mathbb{E}[\omega h_x(x)|\omega < \bar{\omega}] - \phi(x) \\
& \quad - \cancel{f_x(x)}\hat{B} + \mathbb{E}[\theta f_x(x)|\omega > \bar{\omega}] + \mathbb{E}[\omega h_x(x)|\omega > \bar{\omega}] - \phi(x)
\end{aligned} \tag{A.17}$$

When $h_x(X) > 0$, Equation A.17 is always negative. Expected marginal profit is always higher in the good trigger state when shocks are perfectly correlated.

When $h_x(X) < 0$, Equation A.17 is ambiguous. The sign of each line depends on the relative effect between $f_x(X)$ and $h_x(X)$. If the risk effects term dominates then Equation A.17 will be positive. Without further information it is impossible to know which effect dominates. ■

Proposition A.1.1 () *For feasible index insurance contracts specified at either trigger, $\bar{\omega} = 0$ or $\bar{\theta} = 0$, when ω and θ are perfectly correlated random variables, the change in the optimal input is ambiguous when $h_x(x) < 0$ and increases when $h_x(x) > 0$.*

Proof: Perfect correlation implies $\theta < 0$ when $\omega < 0$ and $\theta > 0$ when $\omega > 0$ since both distributions have mean zero, $\mathbb{E}[\theta] \equiv \mathbb{E}[\omega] = 0$. The bounds of the integral can be with respect to either trigger. For simplicity, we will use $\bar{\omega}$ as the trigger, but the proof holds with $\bar{\theta}$.

$$\begin{aligned}
\frac{\partial^2 U}{\partial x \partial \gamma} &= (1 - J(\bar{\omega})) \int_{-\infty}^{\bar{\omega}} \int_{-\infty}^{\bar{\omega}} j(\omega, \theta) u''\left(\pi(x, \hat{B}, \theta, \omega) + (1 - J(\bar{\omega}))\gamma\right) \\
&\quad \times \frac{\partial \pi}{\partial x}(x, \hat{B}, \theta, \omega) d\omega d\theta \\
&\quad - J(\bar{\omega}) \int_{\bar{\omega}}^{\infty} \int_{\bar{\omega}}^{\infty} j(\omega, \theta) u''\left(\pi(x, \hat{B}, \theta, \omega) - J(\bar{\omega})\gamma\right) \\
&\quad \times \frac{\partial \pi}{\partial x}(x, \hat{B}, \theta, \omega) d\omega d\theta.
\end{aligned} \tag{A.18}$$

Suppose insurance fully covers the loss between states, then utility in the good state and bad state are equal to each other so that we can factor out like terms in Equation A.18.

$$\begin{aligned} \frac{\partial^2 U}{\partial x \partial \gamma} &= u''(\cdot) J(\bar{\omega})(1 - J(\bar{\omega})) \\ &\times \left[\int_{-\infty}^{\bar{\omega}} \int_{-\infty}^{\bar{\omega}} j(\omega, \theta) \frac{\partial \pi}{\partial x}(x, \hat{B}, \theta, \omega) d\omega d\theta \right. \\ &\quad \left. - \int_{\bar{\omega}}^{\infty} \int_{\bar{\omega}}^{\infty} j(\omega, \theta) \frac{\partial \pi}{\partial x}(x, \hat{B}, \theta, \omega) d\omega d\theta \right]. \end{aligned} \tag{A.19}$$

By Lemma A.1.1, when $h_x(x) < 0$ the interior is ambiguous so Equation A.19 cannot be signed, but is unambiguously positive when $h_x(x) > 0$. ■

Appendix B

Chapter 2 Appendix

Table B.1: Summary of environmental variables used to predict fishery catch.

	Variable Name	Temporal Resolution	Spatial Resolution	Source
Temperature	Sea Surface Temperature	Monthly	5-km	NOAA Coral Bleaching Degree Heating Week
	Cummulative Habitat Compression Index	Annual	1-degree latitude	Integrated Ecosystem Assessment
Upwelling	Spring BEUTI	Daily	1-degree latitude	Jacox et al., 2018
	Spring CUTI	Daily	1-degree latitude	Jacox et al., 2018
	Frequency	Daily	1-degree latitude	Suca et al., 2022
	Relaxation	Daily	1-degree latitude	Suca et al., 2022
	Spring Transition Index	Daily	1-degree latidue	Suca set al., 2022
Climate	Pacific Decadal Oscillation	Monthly	Regional	PDO ERSST V5
	Oceanic Niño Index	Monthly	Regional	MEI.v2
	El Niño Southern Oscillation Index	Monthly	Regional	ONI
Biological	Squid Paralarvae	Annual	Statewide	RREAS
	Krill Abundance	Annual	Statewide	RREAS

This supplementary document contains summary visualizations of the key indices and the Pearson's correlation to California Market Squid Catch per fisher in metric tons. Data points capture the entire window of observations from 1990-2023. Most indices demonstrate relatively weak correlations with catch. Frequency possess the highest correlation to catch (0.49), while the spring transition index and Pacific Decadal Oscillation had the lowest absolute correlations (0.09).

Parameter sensitivity results of the index insurance contracts to different risk aversion levels and coverage levels are included in tables. Key observations from the main results hold. Fishers are more willing to pay for machine learning models than univariate contracts to protect against weather frequency.

Models with more flexibility were able to predict extreme events more readily. At the coverage level where predicted shocks would exceed 80% of the long run average, SVM and LASSO provided the most amount of protection while remaining profitable for insurance companies (Table B.2).

With higher coverage levels, fishers were more willing to pay for contracts with the same underlying data process. Insurance companies also benefited from more accurate extreme events with lower loss ratios (90%). Protecting more mild deviations led to similar market premiums, but lower loss ratios for insurance companies (Table B.3)

More risk averse fishers are more willing to pay for index insurance contracts. Fishers with mild risk aversion ($\eta = 0.5$) decrease the market premium they are willing to pay across all models (Table B.4). At high levels of risk aversion ($\eta = 3$), market premiums increased by about 12% on average (Table B.5).

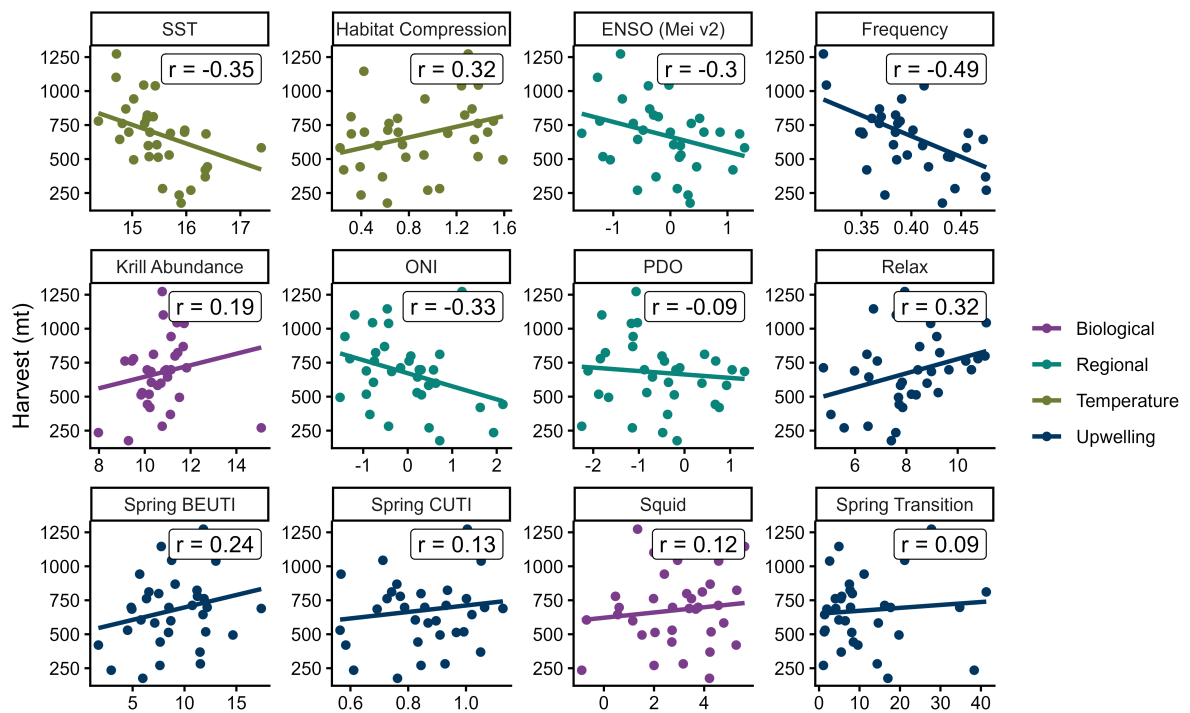


Figure B.1: Pearson's Correlation between weather variables and market squid mt per fisher. Colors correspond to general category of index: Biological (purple), Regional (turquoise), Temperature (green), and Upwelling (blue).

Table B.2: Model performance and utility results when coverage level of contract is set to 80% of average catch. Instances where no payouts are issued in the test set are indicated by “No payouts”. Loss ratios of market premiums that would need to be subsidized are indicated by “-”.

Model	% Utility	Loss Ratio	Train RMSE (mt per fisher)	m^*	Loss Ratio at m^*
SST	0.01	9.1	228.7	1.62	5.6
Spring BEUTI	-0.003	0.00	226.3	No payouts	No payouts
STI	0	No payouts	243.4	No Payouts	No Payouts
Frequency	0.05	3.23	226.1	3.37	0.95
Relaxation	-0.0001	0	238.0	No payouts	No payouts
Spring CUTI	0	No Payouts	236.1	No payouts	No payouts
CHCI	0	No payouts	224.6	No payouts	No payouts
ENSO	-0.001	0	221.8	No payouts	No payouts
PDO	-0.001	0.75	233.5	0.57	-
ONI	-0.03	0	224.0	No payouts	No payouts
Krill	-0.03	0.00	216.0	No payouts	No payouts
Squid	0	No payouts	237.1	No payouts	No payouts
Random Forest	-0.03	0.26	115.8	0.7	-
Regularized RF	-0.07	0.16	133.6	0.12	-
Support Vector Machine	0.08	1.13	144.7	1.73	0.66
LASSO	0.3	2.2	130.2	2.5	0.89

Table B.3: Model performance and utility results when coverage level of contract is set to 90% of average catch. Instances where no payouts are issued in the test set are indicated by “No payouts”. Loss ratios of market premiums that would need to be subsidized are indicated by “-”.

Model	% Utility	Loss Ratio	Train RMSE (mt per fisher)	m^*	Loss Ratio at m^*
SST	-0.013	4.199	228	-	-
Spring BEUTI	-0.031	0.00	226	No payouts	No payouts
STI	0	No payouts	243.4	No payouts	No payouts
Frequency	0.186	4.24	226.1	3.78	1.12
Relaxation	0.015	1.68	238.0	1.1	1.5
Spring CUTI	-0.001	0	236.1	No payouts	No payouts
CHCI	-0.03	0	224.6	No payouts	No payouts
ENSO	-0.04	0.89	221.8	0.39	-
PDO	-0.008	0	233.5	No payouts	No payouts
ONI	-0.03	1.01	224.0	0.64	-
Krill	0.03	0.54	216.0	1.31	0.41
Squid	-0.001	0.00	237.1	No payouts	No payouts
Random Forest	0.05	0.84	115.8	1.21	0.70
Regularized RF	-0.03	0.61	133.6	0.8	-
Support Vector Machine	0.15	1.27	144.7	1.6	0.79
LASSO	0.3	1.78	130.2	1.87	0.96

Table B.4: Model performance and utility results with mild risk aversion $\eta = 0.5$. Instances where no payouts are issued in the test set are indicated by “No payouts”. Loss ratios of market premiums that would need to be subsidized are indicated by “-”.

Model	% Utility	Loss Ratio	Train RMSE (mt per fisher)	m^*	Loss Ratio at m^*
SST	1.8	2.66	228.7	1.8	1.47
Spring BEUTI	-1.9	0.07	226.3	0.11	-
STI	0.03	1.64	243.4	1.38	1.19
Frequency	6	3.96	226.1	3.98	0.99
Relaxation	1.9	2.91	238.0	2.83	1.024
Spring CUTI	-1	0.00	236.1	No payouts	No payouts
CHCI	-1.3	0.64	224.6	0.48	-
ENSO	-1	0.71	221.8	0.61	-
PDO	-1	0.45	233.5	0.31	-
ONI	-0.3	0.89	224.0	0.88	-
Krill	-0.7	0.55	216.0	0.73	-
Squid	-0.8	0.00	237.1	No payouts	No payouts
Random Forest	0.7	1.04	115.8	1.1	0.94
Regularized RF	0.1	1.00	133.6	1.02	0.97
Support Vector Machine	3.5	1.38	144.7	1.45	0.95
LASSO	6	1.68	130.2	1.67	1.01

Table B.5: Model performance and utility results with mild risk aversion $\eta = 3$. Instances where no payouts are issued in the test set are indicated by “No payouts”. Loss ratios of market premiums that would need to be subsidized are indicated by “-”.

Model	% Utility	Loss Ratio	Train RMSE (mt per fisher)	m^*	Loss Ratio at m^*
SST	$-8e^{-5}$	2.66	228.7	0.4	-
Spring BEUTI	$-7e^{-5}$	0.07	226.3	0.42	-
STI	$-2e^{-6}$	1.64	243.4	0.35	-
Frequency	$3e^{-4}$	3.96	226.1	3.5	1.12
Relaxation	$6e^{-5}$	2.91	238.0	2.2	1.31
Spring CUTI	$-1e^{-4}$	0.00	236.1	No payouts	No payouts
CHCI	$-1e^{-4}$	0.64	224.6	0.19	-
ENSO	$-1e^{-4}$	0.71	221.8	0.34	-
PDO	$-1e^{-4}$	0.45	233.5	0.03	-
ONI	$-3e^{-5}$	0.89	224.0	0.8	m
Krill	$9e^{-5}$	0.55	216.0	1.6	0.34
Squid	$-4e^{-5}$	0.00	237.1	No payouts	No payouts
Random Forest	$1e^{-4}$	1.04	115.8	1.36	0.76
Regularized RF	$7e^{-5}$	1.00	133.6	1.21	0.82
Support Vector Machine	$3e^{-4}$	1.38	144.7	1.81	0.76
LASSO	$2e^{-4}$	1.68	130.2	1.38	1.21

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