Index insurance impacts on fishery harvest control rules

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Nathaniel Grimes

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Managers have to balance the needs of fishers with the long term sustainability of fish stocks. Index insurance is a new financial tool that could help managers meet these goals. This paper examines how index insurance could change the optimal harvest control rule for a fishery. The model is a stochastic dynamic programming model that considers both a growth and harvest shock. The model is solved using Value Function Iteration. Preliminary results show that index insurance reduces the optimal harvest control rule at all levels of biomass. Future steps include expanding the model to include basis risk, robustness checks, and simulating the stock and fisher benefits with the new policy function.

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1 Introduction

Fishery management is the primary form of risk mitigation in fisheries (Lane *et al.* 1998; Hilborn *et al.* 2020). Well designed management policies can ameliorate biological and climatic shocks to enhance long term sustainability of fish stocks and fisher income (Cheung *et al.* 2018). However, management policies do not eliminate risk completely, and some actions may be unpopular with fishing constituents (Sethi 2010; Hoefnagel and Vos 2017). Friction exists between managers balancing the long term health of the fish stock with the immediate income needs of fishing communities (Grainger and Parker 2013; Parés *et al.* 2015; Kvamsdal *et al.* 2016).

In extreme circumstances when managers close fisheries due to severe environmental or market distortions, few programs currently exist to alleviate the financial loss of fishers. The Federal Disaster Relief Program provides congressionally approved funds to fishers in the United States (Bellquist *et al.* 2021). European fishers receive assistance through the European Maritime and Fisheries Fund. These programs are often slow to respond, and inequitably distribute proportionally larger funds to industrial vessels than small scale fishers (Jeremy and O'Riordan 2020; Jardine *et al.* 2020).

Index insurance is a promising new financial tool that could address fisher income loss from environmental stochasticity (Watson *et al.* 2023). For example, marine heatwaves can lead to fishery closures (Santora *et al.* 2020; Szuwalski *et al.* 2023). A weather index built on sea surface temperature could trigger payouts for fishers immediately. Index insurance delivers payouts fast and does not require expensive claim verification making it a favorable tool to work in fisheries.

Index insurance contains production risk moral hazards that incentivize fishers to change their harvest. Management provides constraints on these behavior change margins through the use of both input and output controls. Input controls include gear specifications, vessel restrictions, and effort caps while output controls specify total allowable catch (TAC) in the form of quotas or catch limits on the fishery as a whole (Bellido *et al.* 2020). Output controls are defined by harvest control rules where the manager uses stock assessments to determine the current state of the stock and determines allowable catch. Determinations are made on biological or economic goals (Dichmont *et al.* 2010; Free *et al.* 2023). Both sets of controls limit the adaptive margin fishers have to change their harvest in response to insurance payouts. Fishers gain financial security with insurance, and management policies can still meet biological objectives without additional fishing pressure.

However, index insurance could change management policies. Index insurance payouts in years where the manager needs to reduce quota may ameliorate fisher resistance. 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. This paper is the first to examine the influence of index insurance on fishery harvest control rules.

Specifically this research seeks to find how much managers would adjust quota allocations when fishers are protected from different types of risk with index insurance. Additionally, I examine whether insurance contracts that protect from biological or productivity shocks have different impacts on the optimal harvest control rule. Finally, I will compare how much the harvest control rules adjusted to account for insurance improve biological and financial measures of fishery health.

The rest of the paper is structured as follows: Section 2, describes how current harvest control rules set policy under uncertainty. In Section 3 I develop a stochastic dynamic programming model to determine the optimal harvest control rule with and without index insurance. A preliminary model solution is calculated and presented in Section 4 using Value Function Iteration. Initial results indicate index insurance does have an influence on manager HCRs. Future steps for the research are discussed in Section 5. Insurance working in tandem with management may provide stronger outcomes than either tool acting in isolation.

2 Background on stochastic harvest control rules

Fishery managers use harvest control rules to determine the TAC or extraction rules 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 outweight the costs and fisheries that adopt robust HCRs have healthier fisheries (Costello *et al.* 2012; Mangin *et al.* 2018). 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).

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 drastically changes the optimal policy function. Risk aversion leads to policies where quotas are set at more consistent levels regardless of the stock level (Lewis 1981). Kelsall *et al.* (2023) isolated 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. My model will allow for both intertemporal substitution and risk aversion because insurance both smooths income and reduces risk[1]. This will allow us to capture all the effects of index insurance on a managers decision.

No studies to date have used formal insurance programs in fishery harvest control rules. The closest study to this design was done in agriculture by Müller *et al.* (2011). They allowed Kenyan pastoralists to maximize the future stream of welfare with an index insurance contract based on rainfall by choosing the amount of insurance coverage, the amount of pasture to rest in bad years, and the threshold for resting. However, the production choice variables were selected once at the beginning of the year and does not reflect a true harvest control rule. Their insurance moral hazard did influence the choice of pastoralists input decicions, and led to more aggressive resting strategies that could threaten the long term welfare gains of insurance. Adapting a similar framework will help illuminate the effects of index insurance, but adding an optimal policy function allows for more structured adjustments to account for the long term effects.

In the next section I build a new fishery model where managers maximize constituent fishers discounted utility over an infinite time horizon when fishers have access to insurance. My model builds on elements present in previous fishery models, namely Sethi *et al.* (2005), but adds a new layer of complexity by including index insurance.

3 Model

I consider a fishery in discrete time with a single fish stock. The stock, b_t, grows based on the residual escapement, s_t, of fish after harvest h_t and a future stochastic weather shock z^{θ}_{t+1} (Equation 1).

$$\begin{aligned} b_{t+1} &= z^{\theta}_{t+1} G(s_t) \\ s_t &= b_t - h_t \end{aligned} \tag{1}$$

The weather shocks are time independent and the distribution is known to the manager. The manager uses a stock assessment to estimate the current period biomass based on the observed z_t and inform a TAC. Specifically, the TAC establishes the proportion of biomass fishers are allowed to harvest. I choose this specification as it most closely resembles the Actual Catch Limits (ACLs) policy used in the United States. Fisher harvest is random through a stochastic shock z^{ω}_t (Equation 2). The randomness could originate from measurement error in the stock at each period, in season shocks that impact fishing, or the inherent randomness of fishing.

$$h_t = f_t b_t z^{\omega}_t \tag{2}$$

[1] No need for certainty equivalent μ terms

Uncertainty in the current period is captured by z_t^{ω}, and future uncertainty originates from z_{t+1}^{θ}. Each random variables is mean centered at 1 with a known variance $\sigma^2_{\{\omega,\theta\}}$. Both random variables are time independent, but could be correlated with each other. For example, a marine heatwave could reduce the available stock of biomass while simultaneously pushing fish out of common fishing grounds making it more difficult for fishers to locate productive sites. The reduction would be measured by z_t^{θ} while the increased effort to locate fish reflects z_t^{ω}. In general, the shocks will most likely be independent as the growth shock should not impact a measurement error nor would a storm influence the underlying stock. My baseline model will assume the two shocks are independent, but later analysis will relax this assumption as a means to test basis risk in the insurance contracts.

Harvest is sold at the constant world price p and costs are convex in harvest rate. Fishers are risk averse in regards to profit π with concave utility ($u'(\pi) > 0$, $u''(\pi) < 0$).

Insurance will modify fisher utility by ameliorating risk. A simple exogenous insurance contract will payout the difference in observed shocks and the defined trigger $\bar{z}$ times a scale loading γ indicative of the productivity of the fishery (Equation 3). In the exogenous case, γ is fixed at profit when biomass is at maximum sustainable yield. Trigger and scale loading are constant for eternity.[2] Insurance contracts can be defined on either shock.

$$\begin{aligned} I(v) &= \max(0, \bar{z} - z_t^{v})\gamma \\ v &\in \{\omega, \theta\} \end{aligned} \tag{3}$$

Fishers will pay an actuarially fair premium $\rho = \mathbb{E}[I(v)]$ in each period. I assume all contracts perfectly capture their indicies and possess no basis risk. Not all risk will be covered as the other shock will still be present. The insurance will modify utility as seen in Equation 4.

$$\begin{aligned} u_t &= \mathbb{E}[u(\pi_t(f_t, b_t, \omega_t) + \mathbb{I}[(v)])] \\ \mathbb{I}[(v)] &= \begin{cases} I(v) - \rho(v) & \text{if } v_t > \bar{z} \\ -\rho(v) & \text{otherwise} \end{cases} \end{aligned} \tag{4}$$

The manager maximizes the expected infinite stream of expected utility (Equation 5) with discount factor $\beta \in (0, 1)$.

$$\begin{aligned} \max_{f_t} \sum_{t=0}^{\infty} \beta^t \mathbb{E}_t \left[u(f_t, \omega, \theta, I(v)) \right] \\ \text{s.t. } b_{t+1} = z_{t+1}^{\theta} G(b_t - h_t) \end{aligned} \tag{5}$$

[2] I would eventually like to model γ as a choice variable for the manager, but I am concerned about convergence with just one choice. For now, a simple robustness check would be to vary γ from 0 to π_{msy} to see which γ has the highest converged value function

Before I move onto the Bellman formulation of Equation 5, it would be prudent to examine the timing of the model and how the different insurance contracts will play out. An insurance contract built on the biomass growth shock z_t^θ will payout at the beginning of the year before harvest occurs (Figure 1). All the information needed to trigger will be observed by the manager, fishers, and insurance company. Based on the observed z_t^θ and payout $I(\theta)$, the manager will choose a harvest rate f_t. While fishers harvest, the current period shock z_t^ω is observed. The actual harvest will be recorded at the end of the year and the biomass will grow based on the future growth shock z_{t+1}^θ. The manager will then estimate the biomass for the next period and the cycle will continue.

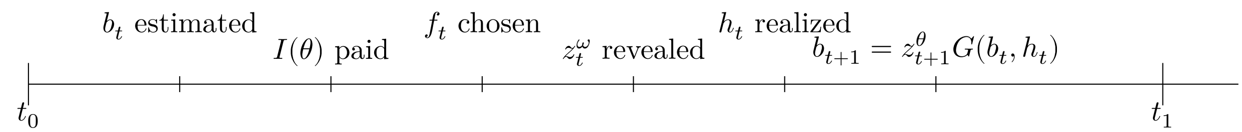

Figure 1: Timing of model when insurance contract triggers on z_t^ω

An insurance contract built on the harvest shock z_{t+1}^ω will payout at the end of the year after harvest occurs (Figure 2). The manager will make harvest choices f_t before knowing whether insurance will benefit fishers. The effects of a pre or post harvest payout could be stark. If the manager knows the stock is in poor condition, they may be more willing to reduce harvest because the fishers are covered from the closure through the insurance. The stock could recover faster through the equation of motion. Alternatively, post harvest payouts may have more subtle influence on how a manager would define the Harvest Control Rule.

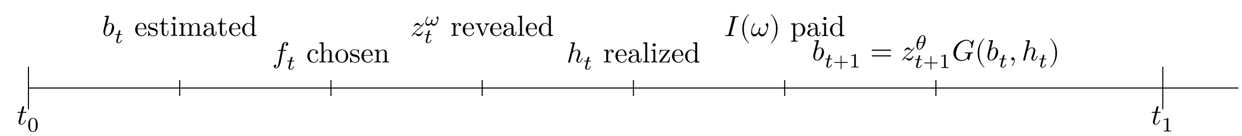

Figure 2: Timing of model when insurance contract triggers on z_t^ω

The Bellman for Equation 5 accounts for uncertainty in both the current and future periods.

$$V(b_t) = \max_{f_t} \mathbb{E}\left[u(f_t, z_t^\omega, z_t^\theta, I(v)) + \beta V(z_{t+1}^\theta G(b_t - h_t))\right] \tag{6}$$

The first order conditions that solve Equation 6 demonstrate how insurance and management could complement each other (Equation 7).

$$\begin{aligned}
&\mathbb{E}[\pi'(f_t, z_t^\omega)U'(f_t, z_t^\omega, z_t^\theta, I(v))] = \beta\mathbb{E}[G'(b_t - h_t)V'(z_{t+1}^\theta G(b_t - h_t))] \\
&\mathbb{E}[\pi'(f_t, z_t^\omega)]\mathbb{E}[U'(f_t, z_t^\omega, z_t^\theta, I(v))] + \text{cov}[\pi'(f_t, z_t^\omega), U'(f_t, z_t^\omega, z_t^\theta, I(v))] \\
&= \beta\mathbb{E}[G'(b_t - h_t)]\mathbb{E}[V'(z_{t+1}^\theta G(b_t - h_t))] + \text{cov}[G'(b_t - h_t), V'(z_{t+1}^\theta G(b_t - h_t))]
\end{aligned} \tag{7}$$

The expected marginal utility gain from current period harvesting (line 2 of Equation 7) must exactly equal the expected marginal utility gain of future fish (line 3 of Equation 7). There are two wealth and investment effects, one for each period. The marginal value of current profit, $\mathbb{E}[\pi']$, is the immediate wealth effect and is matched by future wealth in the marginal value of future fish stocks $\mathbb{E}[G'(b_t - h_t)]$.

The investment effect is more nuanced. The risk fishers take on now, $\text{cov}[\pi', U']$, has a corresponding risk in the future, $\text{cov}[G'(b_t - h_t), V']$, which dictates how much risk fishers are willing to take on now or later. Insurance will affect both these effects. Insurance lowers the variance of utility by equalizing bad and goods states. The covariance of the shocks will lower with less variance in utility. The relative magnitude of reduction in present or future covariance will determine how the harvest control rule is defined. Additionally, it will depend on which wealth effect takes up the margin. Both of these impacts will depend on the type of insurance contract specified. For example, a contract built on current period shocks z_t^{ω} will most likely have a larger impact on the current period investment effect, lowering $\text{cov}[\pi', U']$. Does the manager respond to this reduction by raising immediate harvest to extract more wealth now[3] or does the manager lower harvest in response to the bad state of the world and tradeoff for more future wealth? The complexity of the problem eliminates tractable analytical solutions. In the next section I use numerical methods to approximate the optimal harvest control rule with and without insurance for a manager with risk averse fisher preferences.

3.1 Numerical Solution Methods

Dynamic Programming will find the optimal policy function $f(b^*)$ to define a harvest control rule for each observed b_t. I consider two approaches to solve the model, both use Value Function Iteration. The first approach discretizes the distributions of both shocks into predefined bins using Markov transition probabilities (Figure 3). Then the algorithm iterates over each combination of shocks and states. It maximizes the current expected utility over each z_t^{ω} and the future utility over each z_t^{θ} bin by selecting $f(b^*)$. The algorithm continues to iterate until the value function $V(b)$ converges to the same future value function $V_{t+1}(b)$.

The first approach suffers from the curse of dimmensionality. More precise answers require more bins and states. The search space can become prohibitively large. Approximate dynamic programming uses Monte Carlo simulation to approximate future value functions after decisions are made in the current period (Powell 2011). This setting might be particularly well suited for ADP as I can jointly sample both z_t^{ω} and z_t^{θ} simultaneously. Expected value of insurance needs to be calculated through Monte Carlo simulation. The algorithm will iterate over each b_t to select $f(b^*)$ until the value function converges.

[3]The structure of the current model is implicitly risk increasing in the current period. I would like to introduce risk decreasing specifications, but I worry that the structural form of risk decreasing harvest will not work in value function iteration. The $f^{-\beta}$ adds huge amounts of risk when f is low. So if the manager needs to close the stock for biological purposes, the risk reducing form will never want a closure because the risk will be astronomical.

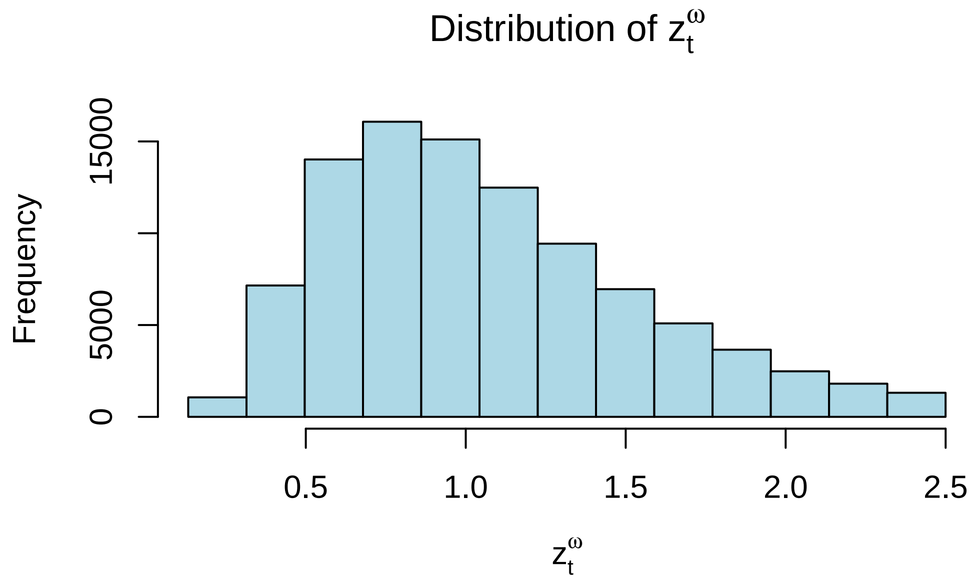

Figure 3: Example of the discretizing the z_t^ω distribution into 13 bins with a log normal distribution and mean 0 and standard deviation 0.5

3.2 Structural forms

I consider two concave utility forms for the fishers: Constant Relative Risk Aversion and Constant Absolute Risk Aversion. When the risk aversion parameter $\eta = 1$ I add a sufficient high constant, k to profits to ensure I do not take negative logs. This will not interfere with the optimization procedure as the marginal utility defines the convergence.

$$u(\pi, I(v)) = \begin{cases} \frac{\pi^{1-\eta}}{1-\eta} & \text{if } \eta \neq 1 \\ \log(\pi + k) & \text{if } \eta = 1 \end{cases}$$

Convex costs are modeled through a squared cost function. The cost parameter c is set to ensure choices of harvest are positive for most levels of fish stock. Harvest is defined above through Equation 2.

$$\pi(f_t) = p f_t b_t z_t^\omega - c f_t^2$$

The growth function is a logistic growth function. The growth parameter r is set to ensure the stock does not go extinct. Carrying capacity K is the upper bound of stock abundance. Next period biomass grows on the residual escapement of fish after harvest $s_t = b_t - h_t$.

$$b_{t+1} = z^{\theta}_{t+1}\left[s_t + rs_t(1 - \frac{s_t}{K})\right]$$

The multiplicative nature of the shocks require distributions with $\mathbb{E} = 1$ and all realizations must be greater than 0. Lognormal distributions provide both properties by ammending the mu parameter of the distribution. Lognormal distributions in expectation are $\mathbb{E}[X] = \exp(\mu + \frac{1}{2}\sigma^2)$. Setting the expectation to 1 and solving for mu in terms of σ^2 allows me to center the distribution around 1 with only positive shocks.

$$z^{\omega}_t \sim \text{Lognormal}(-\frac{1}{2}\sigma^2_{\omega}, \sigma^2_{\omega})$$
$$z^{\theta}_t \sim \text{Lognormal}(-\frac{1}{2}\sigma^2_{\theta}, \sigma^2_{\theta})$$

4 Preliminary Results

I test a quick preliminary run of the model using only the growth shock and the Markov transition probability approach. Index insurance appears to reduce the optimal HCR at all levels of biomass (Figure 4). The new policy function slightly approaches a risk neutral specification. This matches predictions that insurance allows risk averse users to behave more like risk neutral ones.

At all levels of biomass, insurance reduces harvest relative to the risk averse manager with no insurance (Figure 5). The overall effect is small, but the percent difference in harvest can be quite large especially at low levels of biomass. Managers are more inclined to invest in future wealth of the stock if uncertainty in the current period is reduced. Insurance allows managers to purse strategies that reduce harvest pressure on the stock, increasing future value and providing biological conservation.

5 Future Steps

The results of the preliminary analysis are promising, but there remain several steps to complete. The necessary goals are summarized below with strategies to resolve each.

- **Expand to two shock framework**

The model currently only considers the growth shock.

- **Introduce basis risk**

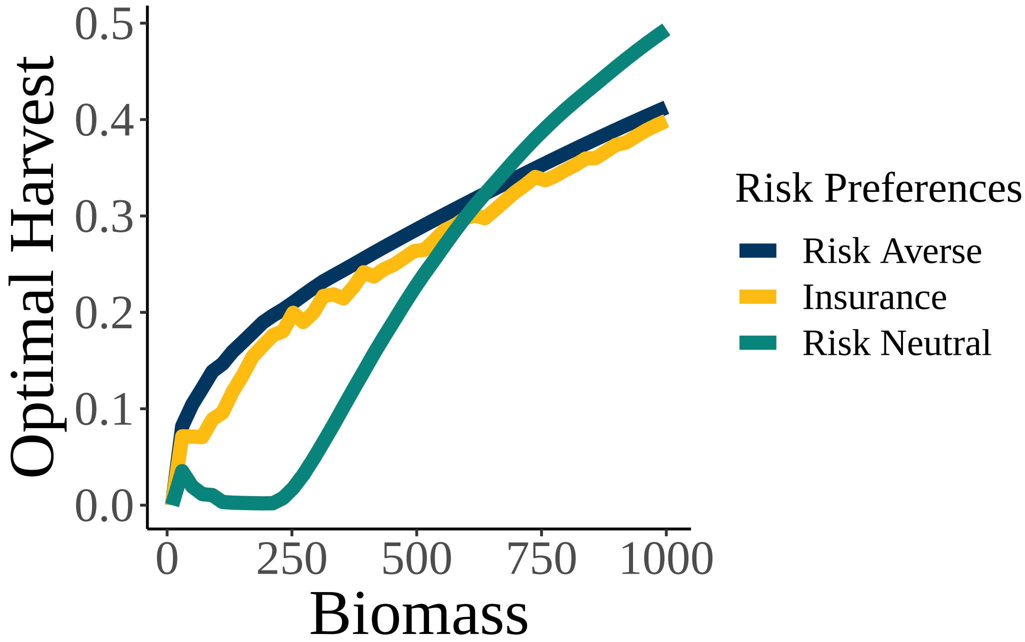

Figure 4: Optimal harvest control rules with insurance (yellow), no insurance (blue), and a risk neutral manager (green) with no insurance.

Allowing the shocks to be correlated with each other can act as a proxy for basis risk. Basis risk is detrimental to the uptake of insurance. Assuming independence implies there will always be a residual amount of risk that cannot be insured. The degree to which the shocks are correlated could impact the structure of the HCR in unexpected ways.

A copula will link the weather variables together for correlation coefficients between 0 and 1. Copulas are preferred in this instant as they allow me to easily specify an correlation and distribution for both shocks. The VFI solutions will sample from the multivariate copula to extract harvest and biological shocks. The VFI procedure will be repeated for each to assess the impact of basis risk on the HCR.

- **Model Robustness Checks**

There are a variety of parameters that need to be checked to understand the full range of impacts insurance will have on the HCR. The amount of insurance γ for either contract needs to be varied to ensure that optimal insurance coverage is selected to not bias the results with over or under insurance. The smoothness of the Value function will determine whether γ could be included as a choice variable in Equation 6. The jaggedness of the converged value function in Figure 4 indicates this may be problematic. Instead, I will vary γ from 0 to pre-insurance profits at Maximum Sustainable Yield levels of biomass to identify an optimal value of γ.

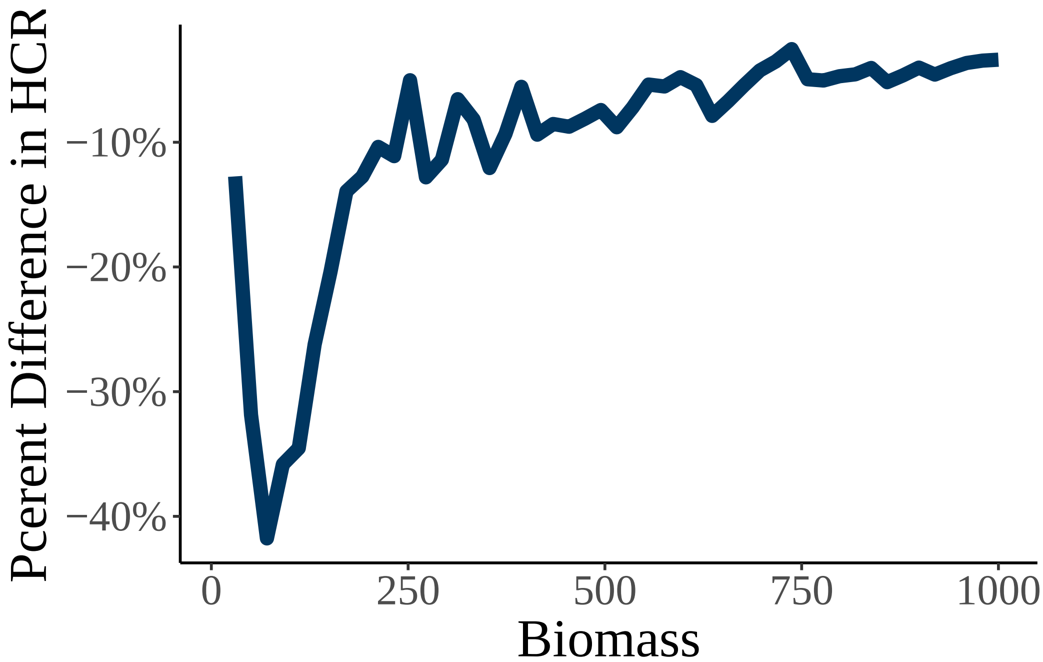

Figure 5: Percent difference in optimal harvest control rules between insurance and no insurance at every level of biomass.

Risk aversion and the time value of utility will also affect the impacts of insurance on the optimal HCR policy. Greater risk aversion may lead to increased insurance value that encourages stronger responses from the manager. The isoelastic parameter η will be varied with reasonable estimates from the financial literature or possibly from studies that calculate fisher risk aversion. The discount rate will also be varied to adjust the time value of money.

Lastly, the relative and absolute amounts of variance from the shocks will be tested assess the changes in the optimal HCR. Sethi *et al.* (2005) showed more variance from measurement error shock that is similar to my z_t^ω has large impacts on the optimal HCR. Insurance mitigates these risks and the amount of correlation between this shows could provide interesting interactions as a result.

- **Simulate the stock and fisher benefits with new policy function**

The model will be simulated with the new policy function to assess the impacts of insurance on the stock and fisher income. Probability of stock extinction after 50 years will be calculated for each optimal insurance policy[4]. Monte Carlo simulation with 1,000 draws of 50 years will use the HCR and growth function to examine the distribution of stock health and fisher utility.

[4]In the event that the HCR do not lead to extinction, I will calculate the mean and variance of stock levels at 50 years

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