Three Essays in Fisheries Economics

Yeuan Chen

A dissertation

submitted in partial fulfillment of the

requirements for the degree of

Doctor of Philosophy

University of Washington

2018

Reading Committee:

Christopher Anderson, Chair

Robert Halvorsen, Chair

Alan Haynie

Program Authorized to Offer Degree:

Economics

University of Washington

Abstract

Three Essays in Fisheries Economics

Yeuan Allen Chen

Chairs of the Supervisory Committee:
Chris Anderson
School of Aquatic and Fishery Sciences
Robert Halvorsen
Department of Economics

The first chapter of this dissertation examines how the sample of catches used by researchers to construct catch expectations proxies is selected by the fisher. We suggest a full information maximum likelihood procedure that can purge the bias from predictions of catch. We find impacts from spatial policies are underestimated, and predictions of catch are overestimated, when selection is ignored. The second chapter investigates how catcher-processors in the Bering Sea pollock fishery can transform larger fish into higher-valued products. By accounting for latent heterogeneity across harvesters, we identify potential increases in fishery profits because some vessels tend to harvest young fish that grow at a faster rate, decreasing the future value of the fishery. The third and final chapter suggests a size-based individual quota policy tool that

allows more fish to be captured by harvesters while simultaneously increasing the size of the fishery biomass.

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ACKNOWLEDGEMENTS

I would like to thank:

Chris Anderson, for turning me into a passable researcher, through many, many years of patient teaching, and prodding, and never giving up.

Robert Halvorsen, whose incisive review was the best preparation for presenting my research I could hope for.

Alan Haynie, for taking a chance on me, an eagerness to collaborate, his invaluable guidance, and congenial walks around Lake Washington, just talking about research.

Levis Kochin, for his generosity, and his willingness to advise on the initiation of this project.

David Layton, for enjoyable and valuable conversations, and a willingness to help.

Joe Cook, whose advice “writing is research” stays with me today.

Members of the Alaska and Northwest Fisheries Science Centers for helpful comments at seminars, and participants at the North American Association of Fisheries Economists and International Institute of Fisheries Economics and Trade conferences for suggestions.

Additional support was provided by Dave Colpo, the Pacific States Marine Fisheries Commission, computing resources at the Center for Studies in Demography and Ecology, and funding through the FishSET Program at the National Oceanographic and Atmospheric Administration Fisheries Office of Science and Technology Economics Program.

All errors remain my own.

DEDICATION

To Kara. The best one.

Chapter 1. CONSTRUCTING CATCH EXPECTATIONS IN FISHERIES DISCRETE CHOICE MODELS

The first chapter of this dissertation examines how researchers construct catch expectations proxies using a sample of catches selected by the fisher. Economic principles from a standard random utility model (RUM) suggest fishers choose locations with the intention of increasing their catch and maximizing their utility. However, fishers have information not known to the researcher when the fisher makes a decision where to fish.

Researchers that construct proxies using non-randomly sampled data, in order to compare expectations of catch at different locations in discrete choice models of fisher behavior, ignore this private information. We illustrate how selection by the fisher biases catch expectation proxies constructed using fishery-dependent data, and how this results in incorrect econometric inference. By using a flexible correction function approach (Dahl 2002), we construct a test for the existence of bias and correct for selection.

We find that full information maximum likelihood estimation can correct the bias in the discrete choice parameters. As an application, we apply the model to the Bering Sea catcher vessel pollock fishery, where we find expected catches are overestimated and the welfare impacts from a spatial closure of the Chinook Salmon Savings Area are underestimated by up to 33 percent on average when selection is ignored.

The second chapter investigates how catcher-processors in the Bering Sea pollock fishery can transform larger fish into higher-valued products. Weight-based harvest quota regulations do not restrict the size of individual fish that fill that quota, although fish of different sizes may present varying profit opportunities and have different impacts on the stock’s growth potential. We empirically link revenue per unit of quota and fish size by investigating the catcher-processor fleet of the U.S. Bering Sea pollock fishery, where larger fish can be made into higher-value fillets, instead of surimi that is lower value on average.

Then, we use a dynamic age-structured model to illustrate how some harvesters target smaller fish to decrease their own harvesting costs, which imposes a stock externality on the fleet. A manager who controls for the size of fish caught in the pollock fishery can increase profits by more than 10 percent, and while part of the benefit is from higher prices coming from higher-value products, more than 75 percent of the increase in fishery value results from a larger biomass.

The third and final chapter suggests a size-based individual quota policy tool that allows more fish to be captured by harvesters while simultaneously increasing the size of the fishery biomass. We develop a dynamic age-structured model to show that non-cooperative harvesters can increase current-period profits by targeting smaller sizes and decreasing costs. Rent dissipation occurs from a reduced rate of biomass growth and fewer large fish in the future, and regulation not differentiated by size fails to prevent these externalities. We propose a policy tool that allocates quota based on the size of fish targeted by harvesters, allowing more fish to be captured while increasing the level of biomass.

1.1 INTRODUCTION

In fisheries models of location choice, decision-makers choose where to fish based in part on their expectations of catch across locations. By capturing how fishers trade off expected catches and costs, researchers can investigate the impacts to fishers from policies such as spatial closures, as well as how fishers will react to these policies. The welfare loss to a fisher depends in part on the expected catches available at alternative locations, as well as the marginal utility fishers derive from those catches (and both must be estimated by the researcher).

However, in these discrete choice models the researcher only observes catches at the location chosen by the fisher. Therefore, researchers must construct proxies of catch expectations, which may be different from the true expectations of fishermen.[1] A method to create proxies is to regress researcher-observed catches on chosen covariates (such as harvester characteristics or lagged

[1] The use of a proxy when expected catches are unobserved by the researcher is common in the fisheries literature, although the construction varies. For example, the expected catch may be as a moving average of historical catches (Eales & Wilen 1986). In each case proxies are constructed using only data observed by the researcher.

catches), and to predict catches at locations unobserved by the researcher using parameter estimates from the model.

A common factor in existing methods to model the spatial decisions of fishermen is the use of fishery-dependent catch data in estimating expected catch at various locations. Examples of such models evaluate how fishers trade off catch and cost expectations (Eales & Wilen 1986), vessel willingness to avoid common-pool bycatch (Abbott & Wilen 2011), the effect of spatial closures and marine reserves (Haynie & Layton 2010, Smith 2005), or the extent of information-sharing across fishermen (Smith 2000), among other topics of study. In this chapter we demonstrate that such catch data is non-randomly sampled and investigate the effect on econometric inference.

The problem of self-selection of data observed by the researcher, and consequently bias in statistical estimation, is a general problem studied in numerous economic models, notably in models of how workers choose their occupation. In the eponymous “Roy Model” self-selection occurs depending on each worker’s endowment of skills (Roy 1951). This intuition has been used to study a number of problems including the choice of schooling (Willis & Rosen 1979), the relationship between earnings and the choice to immigrate (Borjas 1987), and the choice of union employment (Lee 1978), among others. This chapter contributes to the broader literature of modeling and correcting for selection bias (the seminal example a result of Heckman (1979)).

A near-universal assumption in econometric analysis is that the researcher cannot capture every influence on their dependent variable in a regression model, leaving unexplained heterogeneity in the error term of the regression. For example, a fisher may have private information not known to the researcher when they make a decision where to fish. The fisher may be following an aggregation of fish across space, such that they know catches to be large at their next location, even in the absence of visits (and therefore researcher-observed data) at that location.

However, even if the distribution of the error with which researchers estimate expected catch is mean zero, we show that the expected value of that error conditional on observing catch is not. This is because when fishers are more likely to choose locations with larger catches, researchers are also more likely to observe large, positive errors. Biased proxies of expected catch result in incorrect estimates of the impact of catch on fishery utility during discrete choice estimation.

We test and control for this problem by using a correction function approach suggested by Dahl (2002). This approach lends itself to fisheries models of polychotomous choice, as fishers typically must choose between tens to hundreds of locations depending on the scale at which analysts spatially discretize the fishing grounds. In addition, we can test the statistical significance of the correction function in order to ascertain whether self-selection exists in models relying on fishery-dependent data.

In the remainder of this chapter, we first explain how the fisher uses private information about catches when they choose locations, and how expected catch is proxied by the researcher with error due to selection. Then we use Monte Carlo experiments to illustrate how this biases parameter estimates, and how a correction function approach can test and correct for the bias. We find that full information maximum likelihood estimation can completely correct the bias in both the catch equation and estimation of the discrete choice parameters. Finally as an example, we demonstrate the importance of selection in the U.S. Bering Sea catcher vessel pollock fishery by testing whether selection bias occurs using a model relying on fishery-dependent data.

1.2 EXPECTED CATCH WITH ERROR

Consider a stylized model where the catch by weight (Y_{itj}) of fisher i at location j for observation t is a function of vessel-specific covariates (X_i), a location-specific parameter β_j that scales vessel characteristics per vessel ton, and a stochastic catch deviation term u_{itj}, such that:

Equation 1.1: Data-generating process for true catch

$$Y_{itj} = \beta_j * (X_i) + u_{itj}.$$

Catch varies by location and depends on the size of the vessel, and we assume u_{itj} is a normal, independently and identically distributed mean zero random variable, representing the myriad of influences that can impact the fisher's catch that cannot be captured by the researcher's model. Therefore, $\beta_j * (X_i)$ represents the average catch at location j for fisher i, but catch deviates from this average at any given observation.

As a simplifying assumption, we assume that the fisher's expected catch and actual realized catch are the same ($Y_{itj} = E\left[Y_{itj}|I_f\right]$): the stochastic information in u_{itj} is available to the fisher but unknown to the researcher, where I_f and I_r are the information sets available to the fisher and harvester respectively.[2] Because the fisher observes the stochastic catch deviation u_{itj}, fishers have perfect information on the catches at different locations where they consider fishing. Note that we assume the fisher has full information in the fishery without loss of generality: as long as there are variables that affect the decisions of the fisher that are unknown to the researcher, bias resulting from sample selection will exist.[3]

These deviations from location-specific averages occur because fisher-specific knowledge would allow fishers to choose locations when they know the deviations of u_{itj} are positive and catches are larger. For example, more skillful vessel skippers would know when catches are larger than average at a location and act accordingly. Fishers can have private information that catches will be good at their next chosen location despite having not fished there yet, or fishers may share information amongst themselves in a way not observable to the researcher.

However, the researcher only observes realized catches at locations fishers choose, as well as harvester characteristics of those observations (and not β_j). Therefore, the researcher must

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[2] Using this assumption, we will refer to the fisher's expected catch as Y_{itj} in future notation.

[3] We essentially are assuming that $Y_{itj} = E\left[Y_{itj}|I_f\right] \neq E[Y_{itj}|I_r]$, where I_f and I_r are the information sets available to the fisher and harvester respectively. If the fisher also constructs expectations with error, we can construct the catch equation with an error for both the researcher (u_{itj}) and the fisher (τ_{itj}), such that $E\left[Y_{itj}|I_f\right] = \hat{\hat{\beta}}_j * (X_i) + u_{itj}$, where $\hat{\hat{\beta}}_j$ represents the fisher's estimate of how vessel tons scale with catch across locations. Then, the direction of the bias will depend on the relationship between true catch and both expectations (e.g. $Y_{itj} < E\left[Y_{itj}|I_f\right] < E[Y_{itj}|I_r]$). However, as long as $u_{itj} \neq 0$ the researcher's construction will still deviate from the fisher's catch expectation, and bias in the choice parameters will persist.

construct a proxy of expected catch in order to compare locations, without observing the variation from the stochastic error, or knowing the true expectation function.

One method to create proxies of expected catch is to regress researcher-observed catches on known covariates, and use the estimated $\widehat{\beta_J}$ to construct counterfactuals. However, the researcher does not observe the variation in catch expectations at each location, u_{itj}, that is observed by the fisher.

Equation 1.2: Researcher's construction of expected catch

$$E[Y_{itj}|I_r] = \hat{Y}_{itj} = \widehat{\beta_J} * (X_i).$$

Note that Equation 1.2 can be generalized to better match contemporary methods of constructing catch expectations in fisheries economics. Such examples include average catches over a more recent period of time relative to the fisher’s choice occasion (Eales & Wilen 1986), or weighted moving averages of different lag lengths to include both fine-grained and historical information (Abbott & Wilen 2010). We focus on a common approach that can be thought of as a vessel-specific average catch over the entire sample of data available to the researcher.

If the researcher observed catches at all locations, including locations not chosen by the fisher, $\widehat{\beta_J}$ is an unbiased estimator and can be used to construct the fisher’s expected catch at locations the researcher does not observe. In that case, the researcher’s estimate of $\widehat{\beta_J}$, and therefore proxied catch expectations, would be correct on average. However, even if the distribution of the u_{itj} error is mean zero, the expected value of the error on catch *conditional on the researcher actually observing that catch* is not ($E\left[u_{itj}\middle|observe\ Y_{itj}\right] \neq 0$). This is directly a result of the fisher’s choice problem, where they choose locations (and catches) that result in the greatest expected utility at that time.

By examining the underlying intuition in a standard RUM, we can see that researcher-observed catches are not representative of the true catch expectations of fishers. Researchers observe larger catches on average, when fishers are in reality responding to private information at that choice occasion. As a result, researchers overestimate fishers' catch expectations, particularly in locations with smaller true catches, while underestimating differences in expected catch across location. The latter biases researcher estimates of the discrete choice parameters in the fishers' utility.

To see this, the standard random utility model assumes that fishers choose to fish in location j as long as the expected utility in location j, U_j, is greater than the utility in all other locations, or

Equation 1.3: Selection criteria

$$U_j > U_m \ \forall \ m \neq j.$$

If the fisher's utility from alternative j depends on the marginal utility they derive from catch α, vessel- and location-specific variables that are costly to the fisher (Z_{ij}, e.g. travel), a parameter γ that scales cost conditional on vessel characteristics, and a portion of utility unknown to the researcher ε_{itj}, then:

Equation 1.4: Fisher utility

$$U_{itj} = \alpha * (\beta_j * (X_i) + u_{itj}) - \gamma(Z_{ij}) + \varepsilon_{itj}.$$

When the unknown portion ε_{itj} is assumed to be independently and identically distributed extreme value (Gumbel), the true probability fisher i chooses location j can be written as:

Equation 1.5: True probability of choosing location j

$$Prob\left(U_{itj} > U_{itm}, \forall \ m \neq j; \alpha, \gamma, \beta_j, Z_{ij}, X_i\right) = \frac{\exp\left(\alpha/_{\sigma_{scale}} * \left(\beta_j * (X_i) + u_{itj}\right) - \gamma/_{\sigma_{scale}} \left(Z_{ij}\right)\right)}{\sum_{m=1}^{m=M} \exp(\alpha/_{\sigma_{scale}} * (\beta_m * (X_i) + u_{itm}) - \gamma/_{\sigma_{scale}} (Z_{im}))}.$$

Note the fisher's expected catch Y_{itj} depends on the private signal about catch deviations u, and larger catches are associated with greater utility at a location U_{itj}. Larger, positive errors on catch are correlated with the probability that the fisher chooses that location (and the researcher observes that catch).

As a result, on average, the researcher is more likely to observe relatively large, positive realizations of the error on catch because the fisher is more likely to choose locations when the realization of u is larger (and therefore when Y_{itj} and U_{itj}[4] are all larger). As catch enters utility positively in this example of fisheries location choice, we would expect that $E\left[u_{itj}\middle|observe\ Y_{itj}\right] > 0$. Note that this is not a universal truth, but will depend on the data-generating process.

Since expected error in the conditional sample is non-zero, predictions for average catches are incorrect. Denote the catches observed by the researcher $\tilde{Y}_{itj}$. When the final conditional expectation term is not equal to zero (Equation 1.6), regressing researcher-observed catches $\tilde{Y}_{itj}$ on observed covariates to obtain an estimate for $\widehat{\beta_J}$, in order to predict catches $\hat{Y}_{itj}$, results in incorrect inference.

Due to selection, catches observed by the researcher will trend larger than the true average catch at a location, and predicted average catches $\hat{Y}_{itj}$ at each location are biased such that differences between locations are underestimated. Importantly, locations with smaller catches on average are biased to a greater extent, as a fisher would only choose to visit locations with smaller catches on average when there is a relatively large positive catch deviation.

Equation 1.6: Average researcher-observed catches

$$E[\tilde{Y}_{itj}] = \beta_j * (X_i) + \ E\left[u_{itj}\middle|observe\ Y_{itj}\right].$$

When the researcher uses estimates of expected catch based on fishery-dependent data, this bias in the catch equation propagates into estimation of the discrete choice parameters as the researcher

[4] The last by definition.

does not observe expected catches for every location, and tradeoffs across locations are empirically compared by inserting a prediction for the average catch $\hat{Y}_{itj}$ at each location such that:

Equation 1.7: Proxied probability of choosing location j

$$Prob\left(U_{itj} > U_{itm}, \forall\, m \neq j; \alpha, \gamma, \beta_j, Z_{ij}, X_i\right) = \frac{\exp(\alpha/\sigma_{scale} * \hat{Y}_{itj} - \gamma/\sigma_{scale}(Z_{ij}))}{\sum_{m=1}^{m=M} \exp(\alpha/\sigma_{scale} * \hat{Y}_{itm} - \gamma/\sigma_{scale}(Z_{im}))}.$$

1.3 CORRECTING SELECTION BIAS

When the researcher inserts incorrect proxies of catches in the discrete choice problem, they will misunderstand how fishers make tradeoffs between catches and costs. For example, if differences between locations are underestimated, the researcher will overestimate the marginal utility from catch. The researcher observes fishers choosing to move to different locations, incurring travel costs, despite relatively small changes in catch. The model infers fishers must derive large marginal utilities from small changes, when on average the tradeoffs to the fisher are more significant than the proxies imply.

Therefore, the researcher must distinguish between the true expectations of catch fishers use to compare locations that are unobserved by the researcher, and the proxies researchers use to model fisher decisions. How can the researcher create proxies unbiased by selection? Researchers must model fisher expectations of catch as a function of data that is observed by the researcher or that is self-reported by the fisher. However, clearly fishers do not randomly generate the sample of catches to which the researcher fits.

A number of solutions exist (e.g. Heckman & Honore 1990) to correct for selection bias in the sample of catches the researcher uses to create proxies, although they may either require strong distributional assumptions about the error terms, or may not be generalized to models with polychotomous choices.

In a Roy (1952) model estimating how migration is affected by expected earnings across locations, Dahl (2002) suggests a semiparametric correction function, noting that the mean of the conditional error term can be written as an invertible function of the probability that the location was chosen. We apply Dahl's model to correct for selection bias that occurs when expected catches are constructed using fishery-dependent data.

A correction function approach allows us to both test for selection bias as well as estimate unbiased parameters for the catch distribution and choice components. If catches follow the process in Equation 1.1, ($Y_{itj} = \beta_j * (X_i) + u_{itj}$), estimates of $\widehat{\beta_J}$ are obtained by including an approximation of the conditional expectation $E\left[u_{itj} \middle| observe\ Y_{itj}\right] \approx \eta(\widetilde{M}_{itj}, M_{itj}, p_{itj}, \boldsymbol{\beta}_{prob})$ in the regression.

Equation 1.8: Regression with correction function

$$\tilde{Y}_{itj} = \beta_j * (X_i) + \eta(\widetilde{M}_{itj}, M_{itj}, p_{itj}, \boldsymbol{\beta}_{prob}) + v_{itj}.$$

The approximation is a polynomial function of the probability that the chosen location is observed by the researcher (p_{itj}), where $\boldsymbol{\beta}_{prob}$ is a vector of coefficients to be estimated, with each coefficient corresponding to a polynomial term.[5]

$\widetilde{M}_{itj}$ and M_{itj} are indicator variables, the first denoting if the fisher moved or "stayed", and the second to which location they moved. Note that moving or staying is not a nested decision, but rather "staying" denotes the fisher chose the same location (and incurred no moving cost).

As Dahl notes, it would be natural to include probabilities of choosing other locations in the correction function as well, at the cost of increasing the dimensionality, and we follow his suggestion of including the probability of "staying" in the correction function. It is feasible to include only the probability of the chosen location as long as this probability conveys all information about catches in a chosen location, a condition Dahl refers to as the index sufficiency assumption.

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[5] For example, a 3rd order polynomial correction function for a fisher that stayed at location *j* could be written as $c + \beta_{prob1} * p_{itj} + \beta_{prob1} * p_{itj}^2 + \beta_{prob3} * p_{itj}^3$, where $\boldsymbol{\beta}_{prob}$ and constant c are estimated, and the probabilities p_{itj} of fisher *i* staying at location *j* are included as covariates.

Therefore, we include a separate correction function for each location where a fisher moves, and for each location where a fisher "stays". With *J* locations there are therefore a total of *J*2* correction functions. Note that v_{itj} is an error term with mean zero in the *conditional* sample and u_{itj} is estimated as a function of the probability of moving to or staying at location *j*.

Equation 1.9: Correction function

$$\eta(\widetilde{M}_{itj}, M_{itj}, p_{itj}, \boldsymbol{\beta}_{prob}) = \widetilde{M}_{itj} \sum_{j=1}^{J}[M_{itj} * \eta_{itj}(p_{itj})] + (1-\widetilde{M}_{itj}) \sum_{j=1}^{J}[M_{itj} * \eta_{itj}(p_{itj})] =$$
$$\widetilde{M}_{itj} \sum_{j=1}^{J}[M_{itj} * (\sum_{n=1}^{n=N} \beta_{prob,j,n} * {p_{itj}}^{n} + \sum_{\tilde{n}=1}^{\tilde{n}=N} \beta_{prob,j,\tilde{n}} * (p_{itj}\tilde{p}_{itj})^{\tilde{n}}))]$$
$$+ (1-\widetilde{M}_{itj}) \sum_{j=1}^{J}[M_{itj} * (\sum_{n=1}^{n=N} \beta_{prob,j,n} * {\tilde{p}_{itj}}^{n})]$$

The selection bias for each location is approximated with a polynomial function of *n* degrees. The probability that harvester *i* chooses location *j* is denoted ${p_{itj}}^{n}$, while the probability that they stay is denoted ${\tilde{p}_{itj}}^{n}$, where *n* is the power of the polynomial. Also note that in the correction function for movers, the polynomial of the moving probability and the polynomial of the interaction term need not be the same degree ($n \neq \tilde{n}$).

The polynomial is then included in the ordinary least squares estimation of the catch equation. This semiparametric correction has been employed in a number of studies, such as examining how Ecuadorians migrated to the United States or Spain after the 1999 economic crisis (Bertoli et al. 2013), estimating the magnitude of a college premium in wages (Carneiro & Lee 2011), or examining how the introduction of the personal computer affected the return to education from 1980-2000 (Beaudry et al. 2010).

By approximating the conditional error term with a polynomial function, and including it in the catch regression, we can purge the bias in $\widehat{\beta_J}$ and therefore obtain unbiased predictions of expected catch, which leads to accurate estimation of the discrete choice parameters. In addition, an advantage to using the correction function approach is that we can estimate the statistical significance of the correction functions. When the correction terms jointly are statistically significant, they indicate whether the conditional error is significantly different from zero, and whether self-selection occurs in the sample of data available to the researcher.

1.4 FULL INFORMATION MAXIMUM LIKELIHOOD ESTIMATION

Dahl suggests estimating probabilities by creating "cells", where individuals within a cell have similar characteristics. Individuals with different characteristics are assumed to also be more or less likely to move to a given location, on average. We note however that the probabilities can also be recovered from the discrete choice problem. One reason not to use these probabilities in a two-stage approach is that conditional logit estimates often suffer from the independence of irrelevant alternatives assumption.

Instead of estimating the probabilities first, and inserting them into the correction function, we suggest an extension of Dahl's correction function approach by simultaneously estimating the corrected catch equation with the discrete choice problem using full information likelihood, and find better performance in correction of the bias.[6] The full likelihood that fisher *i* chooses location *j* is:

Equation 1.10: Full likelihood function

$$l_{itj} = \left(\frac{2\pi^{-n/2}}{\sigma_{catch}^{n}} \exp\left[\frac{-\Sigma\left(\tilde{Y}_{itj} - \beta_j * (X_i) - \eta\left(\widetilde{M}_{itj}, M_{itj}, p_{itj}, \boldsymbol{\beta}_{prob}\right)\right)^2}{2\sigma_{catch}^2}\right]\right) *$$

$$\left(\frac{\exp({}^{\alpha}/_{\sigma_{scale}} * \beta_j * (X_i) - {}^{\gamma}/_{\sigma_{scale}}(Z_{jk}))}{\sum_{m=1}^{m=M} \exp({}^{\alpha}/_{\sigma_{scale}} * \beta_m * (X_i) - {}^{\gamma}/_{\sigma_{scale}}(Z_{mk}))}\right).$$

The probabilities p_{itj} in the correction function of the catch equation are no longer estimated first, then fixed, but rather updated as a function of the parameters in the fisher's utility. Specifically, take advantage of the fact that the probability of choosing a location (or staying in the original location can be calculated as part of the full likelihood:

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[6] An example of joint estimation of catch and location choice is the expected profit model of Haynie and Layton (2010), although we explicitly correct for selection in our problem.

Equation 1.11: Probability of choosing location j

$$(Prob\big(U_{ij} > U_{im}, \forall\, m \neq j; \alpha, \gamma, \beta_j, Z_{ij}, X_i\big) = \frac{\exp(^{\alpha}/_{\sigma_{scale}} * \hat{Y}_{itj} - ^{\gamma}/_{\sigma_{scale}}(Z_{ij}))}{\sum_{m=1}^{m=M} \exp(^{\alpha}/_{\sigma_{scale}} * \hat{Y}_{itj} - ^{\gamma}/_{\sigma_{scale}}(Z_{im}))}).$$

Then, the correction function portion in the likelihood can be written as:

Equation 1.12: Correction function in likelihood

$$\eta\big(\widetilde{M}_{itj}, M_{itj}, p_{itj}, \boldsymbol{\beta}_{prob}\big) = \widetilde{M}_{itj} \sum_{j=1}^{J} [M_{itj} * \eta_{itj}(p_{itj})] + (1 - \widetilde{M}_{itj}) \sum_{j=1}^{J} [M_{itj} * \eta(p_{itj})] =$$

$$\widetilde{M}_{itj} \sum_{j=1}^{J} [M_{itj} * (\sum_{n=1}^{n=N} \beta_{prob,j,n} * {p_{itj}}^{n} + \sum_{\tilde{n}=1}^{\tilde{n}=N} \beta_{prob,j,\tilde{n}} * (p_{itj}\tilde{p}_{itj})^{\tilde{n}}))]$$

$$+ (1 - \widetilde{M}_{itj}) \sum_{j=1}^{J} [M_{itj} * (\sum_{n=1}^{n=N} \beta_{prob,j,n} * {\tilde{p}_{itj}}^{n})],$$

$$\text{s.t. } {p_{itj}}^{n} = \left(\frac{\exp(^{\alpha}/_{\sigma_{scale}} * \hat{Y}_{itj} - ^{\gamma}/_{\sigma_{scale}}(Z_{ij}))}{\sum_{m=1}^{m=M} \exp(^{\alpha}/_{\sigma_{scale}} * \hat{Y}_{itj} - ^{\gamma}/_{\sigma_{scale}}(Z_{im}))}\right)^{n}.$$

Note that if the correction is successful and the parameters β_j are estimated without bias, the researcher is comparing unbiased estimates of average catch across locations in the discrete component of the likelihood.[7] The estimated correction $\eta(\cdot)$ varies across individual fishers, across chosen locations, and depending on whether the fisher moved or stayed, as it is a function of the indicator variables $\widetilde{M}_{itj}$ and M_{itj}, as well as the probabilities p_{itj} that are updated as a function of the parameters in the fisher's utility, which depend on fisher characteristics. We can then simultaneously estimate β_j, α, and σ_{scale} and we find that full information maximum likelihood estimation performs better at correcting the bias in both the catch and discrete choice components of the likelihood, compared to two-stage methods.[8]

[7] Note that comparing actual realized catches across locations for a single observation is not feasible, because the correction $\mu(\cdot)$ approximates the expected realization of the catch deviation given that the researcher observed the catch ($E\big[u_{itj}\big|observe\ Y_{itj}\big]$), and not the realization of the catch deviation at every single observation. In addition, the correction polynomial is not included in the discrete component of the likelihood, because inclusion of the correction implies the researcher would be incorrectly comparing $E\big[Y_{itj}\big|observe\ Y_{itj}\big]$, with $E[Y_{itm}|observe\ Y_{itm}]$ $\forall\, m \neq j$. Instead, we include the correction in the catch portion of the likelihood to obtain unbiased estimates of average catch, and then compare unconditional expectations of catch across locations.

[8] Again fixing γ and estimating the scale parameter for the purposes of comparing α.

Previous literature typically estimates a first-stage regression with correction, and inserts predicted values using the first-stage estimates in a second-stage equation of interest. The second-stage equation may be a linear function (e.g. examining the magnitude of migration flows in Dahl 2002) or a discrete choice problem (Bertoli et al. 2013). To our knowledge, the first-stage with correction has not been modeled jointly with the second-stage problem.

1.5 MONTE CARLO EXPERIMENT ILLUSTRATES HOW ESTIMATES ARE BIASED

We begin by using a stylized model in a Monte Carlo experiment to demonstrate that fishers choose locations based on private information not known to the researcher, and this biases estimates of the marginal utility from catch in random utility models of location choice. For the data generating process let there be *J=4* locations in our experiment, where catch and utility vary across locations. Then, a given fisher *i* that is currently in location *k*, chooses between *J* potential utilities:

Equation 1.13: Monte Carlo expected utility

$$U_{itjk} = \alpha * Y_{itj} - \gamma(distance_{jk} * hp_i) + \varepsilon_{itjk} .$$

Costs depend on the distance from their current location *k* to potential location *j*, and this distance depends on their current location (*k*). In addition, distance is interacted with a harvester characteristic (for example vessel "horsepower" hp_i), e.g. vessels with more horsepower may have higher or lower costs of travel. We randomly generate uniformly distributed variables for horsepower such that $hp_i \sim U[1,10]$; note that the scale of the distribution is chosen for convenience and is generalizable as long as costs are scaled appropriately to the other variables in fisher utility (for example by scaling the γ coefficient on distance).

Fishers choose locations on a square grid, where the Euclidean distance to the adjacent grid square is parameterized to be 1.5 units.[9] In addition, ε_{itjk} is distributed Extreme Value Type I ($G(0,1)$) with mean equal to the Euler-Mascheroni constant (0.5772) and variance equal to $\pi^2/6$.

We assume catches follow:

Equation 1.14: Monte Carlo catch equation

$$(Y_{itj} = \beta_j * (tons_i) + u_{itj}),$$

where fishers in vessels with greater tonnage catch more fish on average. The harvester characteristic $tons_i$ is distributed $U[1,5]$,[10] while the error on the researcher's catch regression u_{itj} is normally distributed ($N(0,3)$). The fisher observes Y_{itj} for all i, and chooses a location based on its observation, while the researcher constructs $\hat{Y}_{itj} = \hat{\beta}_j * (tons_i)$ as described in Section 1.2. The true catch coefficients β_j are described in Table 1.2.

The estimated probability that the fisher chooses location j is:

Equation 1.15: Monte Carlo estimated probability fisher chooses location j

$$Prob\left(U_{itj} > U_{itm}, \forall\, m \neq j; \alpha, \gamma, \beta_j, distance_{jk}, hp_i, tons_i\right) = \frac{\exp(\alpha/\sigma_{scale} * \hat{Y}_{itj} - \gamma/\sigma_{scale}(distance_{jk} * hp_i))}{\sum_{m=1}^{m=M} \exp(\alpha/\sigma_{scale} * \hat{Y}_{itm} - \gamma/\sigma_{scale}(distance_{mk} * hp_i))}.$$

Because the scale parameter σ_{scale} cannot be identified, for the purposes of comparison in the Monte Carlo experiments we fix the cost parameter γ to its true value[11], and estimate the catch and

[9] And the distance to the diagonal location is 2.12 units.

[10] Again note that we've chosen the scale of the distribution without loss of generality, as other variables and coefficients (such as α or β_j) in the fishery utility can be appropriately scaled if the harvester characteristic were to be changed.

[11] The true value of γ is -1.

scale parameters α and σ_{scale}, comparing the catch parameter to its true value to determine the magnitude of bias.

Because true catches are not observed by the researcher at every location for a given observation, we first estimate β_j in a first-stage regression, then use $\hat{\beta}_j$ to create proxies of catch $\hat{Y}_{itj}$, which are inserted in the fisher's utility for the discrete choice second-stage, and estimated using conditional logit.

We generate 1000 choice occasions at each initial location *k*, where fishers on each choice occasion choose between j utilities and catches, given randomly drawn fisher characteristics, and the fisher chooses the location according to the selection criteria in Equation 1.3 ($U_j > U_m \; \forall \; m \neq j$). Note this model does not include or account for state dependence or dynamic choice: researchers observe a number of haul occasions, the locations chosen, the catches at the chosen locations, and the location of the previous haul.

1.5.1 *Uncorrected results*

As a baseline, first note that when the private signal u_{itj} is absent in fisher catch expectations, conditional logit[12] produces unbiased estimates of α, where the true parameters are given in the last column, on 100 Monte Carlo iterations.

Table 1.1: Conditional logit without error in catch

	Estimated parameter	**Standard error**	**True parameter**
$\boldsymbol{\alpha}$	2.99	0.03	3.00

[12] All discrete choice estimation is performed using modified routines from the FishSET toolbox.

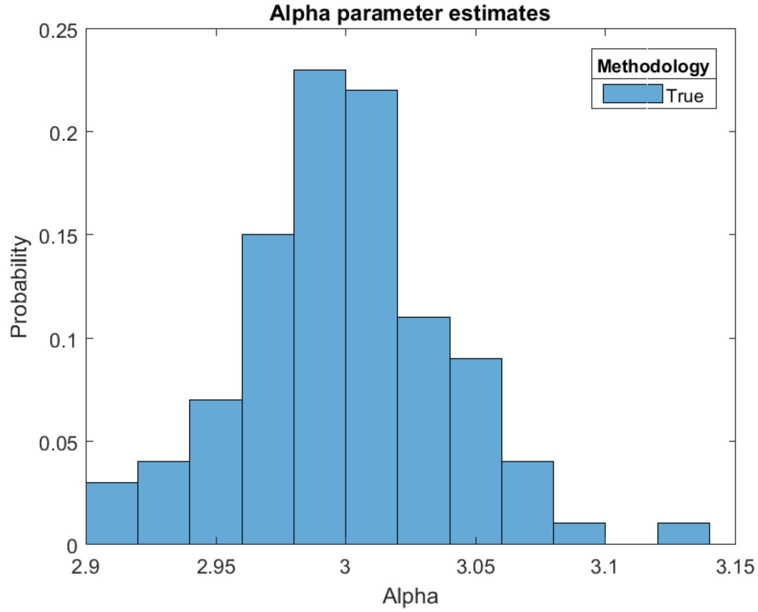

Figure 1.1: Baseline model without private signal, discrete choice estimates

Next, when we introduce error in the catch equation, estimates for catch are significantly larger than the true means, and this bias in catch holds true regardless of the data-generating process. Fishers will choose locations with a smaller true mean whenever the private signal is positive and large for that time period. Researchers observe the catch plus the private signal, and the sample of catch data tends larger. In addition, because mean catches are heterogeneous across vessels (as vessels with larger tonnage catch more fish), vessels self-select into locations given their characteristics.

Table 1.2: Catch equation with error

Location	**Estimated parameters**	**Standard error**	**True parameters**	**Bias**
$\boldsymbol{\beta_1}$	2.01	0.02	1.50	0.51
$\boldsymbol{\beta_2}$	1.88	0.02	1.25	0.63
$\boldsymbol{\beta_3}$	1.75	0.02	1.00	0.75
$\boldsymbol{\beta_4}$	1.61	0.03	0.75	0.86

Note that when we estimate catch according to Equation 1.1, without correction, the bias is not proportional across locations (for each estimated beta). This is important because the selection bias does not fall out of the probability in a second-stage conditional logit estimation, when we use the estimated betas to create predicted catch values as proxies. The bias tends larger at less productive locations with smaller average catches.

In addition, researcher-observed catches trend more similarly across locations on average than fisher expected catches (that are not observed by the researcher). Differences across locations are underestimated. This matches empirical data patterns in many fisheries where catches are "hyperstable", and do not change much across locations. However, note that in our model the true mean across locations varies. This hyperstability is a result of selection, and not the true underlying process generating catches.

For instance, imagine again a researcher observing a fisher following an aggregation of fish across locations, resulting in stable catch levels. The researcher would proxy expected catches similarly across space, when in reality, at the time of selection, expected catches were not similar to the fisher. Predicted catches would be overestimated, while tradeoffs such as from a spatial closure would be underestimated. We examine possible welfare effects in our empirical example below (Section 1.6).

Table 1.3: Conditional logit with error in the catch equation

	Estimated parameters	**Standard error**	**True parameters**
$\boldsymbol{\alpha}$	5.89	0.58	3.00

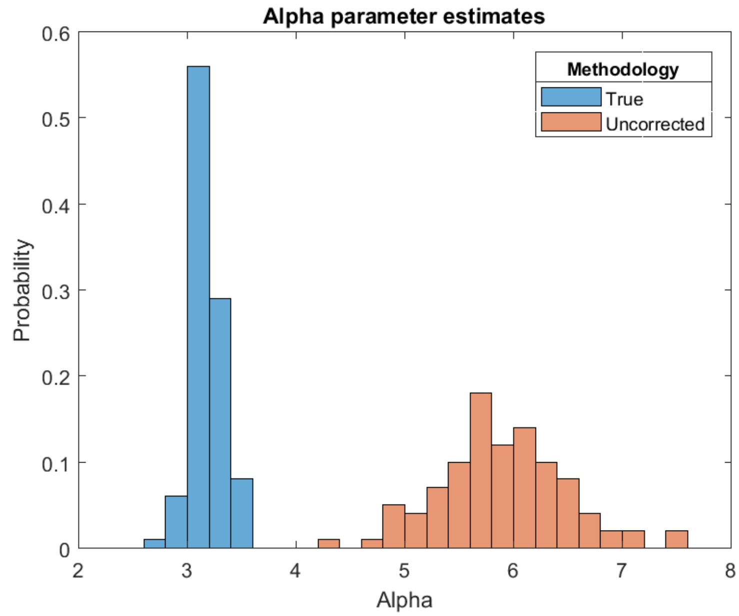

Figure 1.2: Uncorrected discrete choice estimates

In this data-generating process, because differences in catch across locations are underestimated, the impact of catch on fisher utility is overestimated in the conditional logit step in Table 1.3, where we compare incorrectly proxied catches with proxies constructed with the true βs. Proxied counterfactual catches are more similar to each other across locations than the true catches the fisher observes. The researcher incorrectly believes the fisher is willing to move to locations for small increases in catch, while the true fisher expectation at those locations is actually larger. We examine causes for the direction of the bias in catch on fisher utility below (Section 1.5.5), as we show the direction of the bias in the marginal utility of catch can be negative, and depends on the similarity across locations and sample size available to the researcher.

1.5.2 *Correction function approach*

Then, as described in Section 1.3, for each location we estimate a separate "stayer" correction function for observations that stayed in the same location as their previous haul, and another for observations that moved to a new location (a "mover" correction function). This results in *k*2* correction functions, or in our Monte Carlo experiment, 8 total correction functions. Each correction function is a polynomial, and we choose to model the stayer correction function as a 5^{th}-order polynomial in the retention probability, and the mover correction function as a 5^{th}-order polynomial in the probability of moving to the given location, with a 2^{nd}-order polynomial in the interaction between the probability of moving and the probability that they stayed.[13]

Because in fisheries discrete choice models the researcher can exploit repeated observations from each fisher, we calculate probabilities as the proportion of observations in which each vessel visits a given location (treating each individual vessel as a "cell"). We estimate the corrected catch equation in a first stage, then create proxies based on that estimation, which are inserted in to the discrete choice problem in a second stage.

Table 1.4: Catch equation with correction function

Location	**Estimated parameters**	**Standard error**	**True parameters**	**Bias**
$\boldsymbol{\beta_1}$	1.41	0.04	1.5	-0.09
$\boldsymbol{\beta_2}$	1.23	0.05	1.25	-0.02
$\boldsymbol{\beta_3}$	1.06	0.06	1	0.06
$\boldsymbol{\beta_4}$	0.89	0.07	0.75	0.14
F-test[39,3957]	33.19			

The correction function reasonably approximates the conditional error term, and location-specific means revert to their true values. In addition, an F-test implies the data is inconsistent with the hypothesis that the correction function terms are equal to zero. Because the private signal in the uncorrected catch equation is proxied by the correction function, we can conclude that selection bias occurs in this simulated fishery as the terms of the selection function are jointly significant (they are statistically different from zero).

Then, we use our estimates from our catch regression to proxy counterfactual catches across locations in a second stage discrete choice model (Bertoli et al. 2013). We find that while the

[13] We find the choice of polynomial is robust to smaller-order polynomials (as low as 2^{nd}-order polynomials), and the use of larger-order polynomials is at the cost of efficiency.

corrected estimates improve the conditional logit estimates of the cost and catch coefficients, they cannot completely correct the second-stage bias. We can compare the difference between two-stage and full-information estimation in next section (1.5.3).

Table 1.5: Conditional logit with corrected catch

With correction	**Estimated parameters**	**Standard error**	**True parameters**
α	4.36	0.66	3.00
Without correction	**Estimated parameters**	**Standard error**	**True parameters**
α	5.89	0.58	3.00

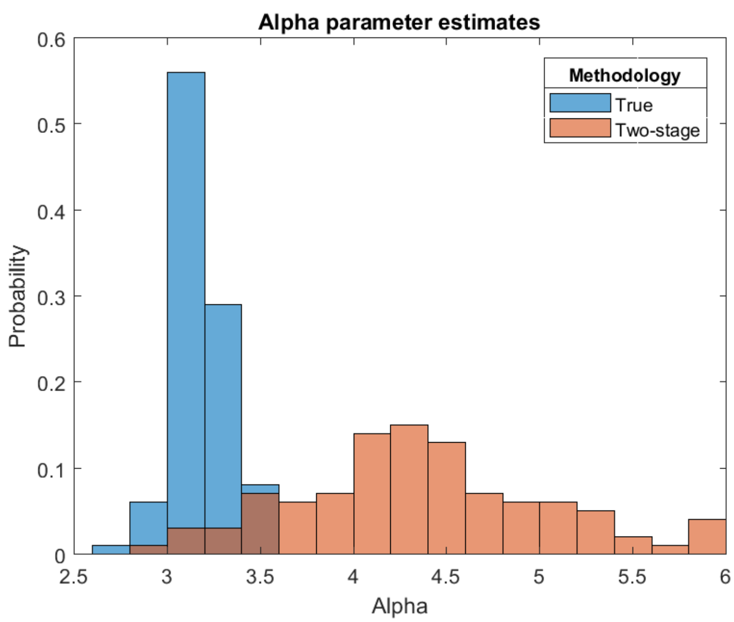

Figure 1.3: Corrected discrete choice estimates

1.5.3 *Joint estimation*

Our proposed methodology jointly estimates the discrete choice portion of the likelihood with the corrected catch function, and we find it performs significantly better than two-stage methods. We find that the selection bias in the catch equation is almost completely corrected, while estimates of the marginal utility from catch appear both unbiased and consistent.

Table 1.6: Full information maximum likelihood with corrected catch

Location	Estimated parameters	Standard error	True parameters	Bias
$\boldsymbol{\beta_1}$	1.49	0.02	1.50	-0.01
$\boldsymbol{\beta_2}$	1.24	0.01	1.25	-0.01
$\boldsymbol{\beta_3}$	0.99	0.02	1.00	-0.01
$\boldsymbol{\beta_4}$	0.73	0.02	0.75	-0.02
$\boldsymbol{\alpha}$	3.13	0.42	3.00	0.13

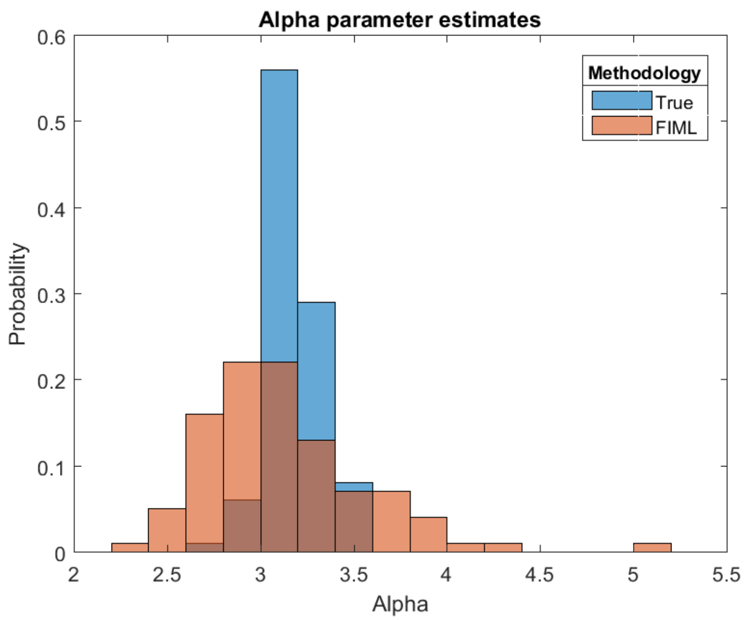

Figure 1.4: Full information maximum likelihood discrete choice estimates

Jointly deriving the probabilities used in the correction function with the discrete choice component of the likelihood appears to significantly improve fit. Because the second-stage equation of interest is often not the discrete choice problem itself in Roy models of migration, joint estimation to our knowledge has not been investigated in this literature. However, we show that estimates of the first-stage catch equation are also improved, because small differences in the catch parameters can result in relatively large biases in the discrete choice estimates.

When we estimate the correction function in a first stage, we consistently overestimate locations with true larger catches, and underestimate locations with true smaller catches (Table 1.4). The model infers observed movement as a result of relatively small differences in catch, when movement is actually in part due to private information known only to the fisher, and this results in estimates of fisher catch expectations that underestimate differences across locations.

Here, the impact of underestimating the *differences* across locations is to overestimate α. Intuitively, because we proxy catches at locations to be more similar to each other than they truly are, we incorrectly believe fishers choose to move to locations even though catches are relatively similar, which the uncorrected model interprets as evidence of a large marginal utility from catch. While the two-stage corrected methods largely correct the selection bias, the remaining structure that it is unable to purge has a significant effect on the discrete choice parameters.

1.5.4 *Bounding the efficacy of full information maximum likelihood*

As a result, we find that full information maximum likelihood performs well even as we increase the variance of the error term in the catch equation. We repeat the Monte Carlo experiments above, re-estimating the model (and correction functions) as we increase the private information available to the fisher relative to average catches, and find that joint estimation is robust as selection bias increases. Notably, both the two-stage and uncorrected methods perform worse as the private signal becomes larger.

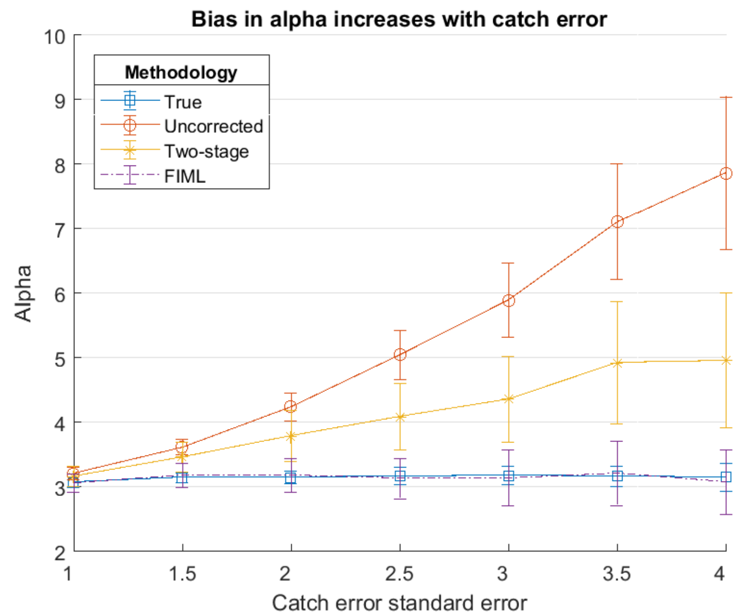

Figure 1.5: Bias in discrete choice estimates

While the two-stage correction estimator can correct some of the bias in the first-stage, and improve estimation of the discrete choice parameters, they still overestimate the impact of catch on fisher utility in this example, because differences across locations are still underestimated. We find small errors in the catch equation can have large effects in the second stage, in particular when there is structure in the error (here from underestimating differences). However, full-information maximum likelihood estimation behaves well even as the variance of the error term increases.

1.5.5 *Explaining the direction and magnitude of the bias*

To understand the direction of the bias we must examine the inaccuracy of the parameter estimates in the catch equation, in conjunction with the true data-generating process dictating how similar locations are. In Figure 1.6 we introduce bias in each catch parameter, while holding the other catch equation parameters (β_i) constant. At first, introducing a small amount of positive bias to locations with larger catches (e.g. β_1) underestimates the impact of catch on utility (α), while positive bias in locations with smaller catches overestimates α. The converse is true of introducing negative bias across locations. Note that if bias in the catch equation parameters (β_i) was in the same direction and identical across β_i, there would be no bias in estimating α.

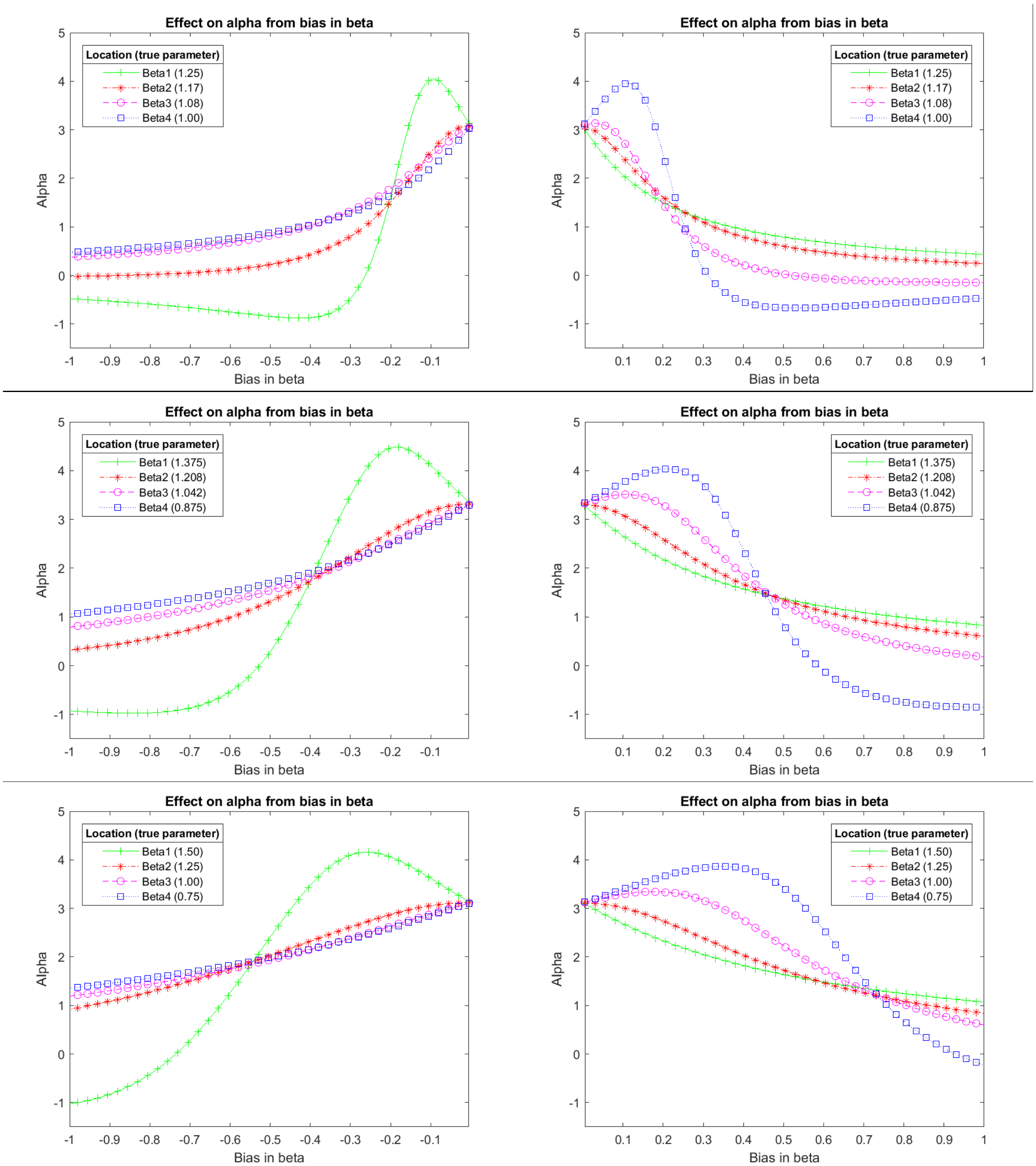

Figure 1.6: Bias in catch equation parameters

At first, underestimating β_1 biases α upwards (for a small amount of bias, i.e. approximately -0.2 in the first row of Figure 1.6). Meanwhile, overestimating β_3 and β_4 also biases α upwards.

However, as the bias increases, the sign of the bias changes. For example, positive bias in β_4 biases the marginal utility of catch upwards until the bias in β_4 is equal to approximately 0.2 in the first panel. Then, as the amount of bias increases, the sign of the bias in the marginal utility from catch (α) changes - e.g. the bias in α, as positive bias in β_4 increases, is concave.

Furthermore, note that as true differences across locations become more disparate (following the plots down the page vertically), a larger bias in β_i is required before the sign of the bias in the marginal utility from catch (α) changes direction. This is because the change in the direction of the bias occurs when the researcher incorrectly changes the ordinal ranking of the locations by quantity of catch. For example, if the researcher overestimates β_4 to the extent they believe expected returns from that location are larger than the location corresponding to β_1.

If the researcher observes vessels abstaining from visiting the location corresponding with β_4, even though catches are (incorrectly) predicted to be larger there than all other locations, the model will infer vessels must suffer disutility from larger catches, flipping the sign on estimates of the marginal utility from catch (α). Differences across locations are no longer underestimated, but rather the ordinal ranking of locations by expected catch has changed - locations with small catches are estimated to have large catches, and vice versa.

Importantly, the change in the direction of the bias manifests when parameter estimates in the catch equation are inaccurate due to a small number of observations across locations.[14] Table 1.7 shows an example of average parameter estimates in the catch equation, as well as the standard deviation of those estimates across Monte Carlo iterations, as the number of observations per location increases.

Unsurprisingly, when the researcher has few observations their estimates are inaccurate. We refer to locations with larger average catches as "productive" locations, and locations with smaller average catches as "unproductive" locations. Then, when locations are similar and estimates of β_i

[14] The intuition here more closely follows the results found by Morey and Waldman (1998), who investigated the impact of measurement error on discrete choice modeling. They suggest a correction based on the fact that the number of choices observed for a location provides information on expected catches at that location.

are inaccurate, the researcher may observe unproductive locations with larger absolute catches than productive locations due to chance (due to sampling variability).

Table 1.7: Average catch equation parameters and standard deviations

Number of observations	**30**	**60**	**100**	**200**	**400**
Average estimate ($\boldsymbol{\beta_1 = 1.25}$)	1.85	1.86	1.85	1.86	1.86
Standard deviation ($\boldsymbol{\beta_1}$)	*0.12*	*0.10*	*0.09*	*0.05*	*0.03*
Average estimate ($\boldsymbol{\beta_2 = 1.17}$)	1.82	1.83	1.81	1.81	1.82
Standard deviation ($\boldsymbol{\beta_2}$)	*0.15*	*0.11*	*0.09*	*0.06*	*0.03*
Average estimate ($\boldsymbol{\beta_3 = 1.08}$)	1.77	1.77	1.78	1.77	1.78
Standard deviation ($\boldsymbol{\beta_3}$)	*0.16*	*0.09*	*0.08*	*0.05*	*0.04*
Average estimate ($\boldsymbol{\beta_4 = 1.00}$)	1.73	1.73	1.73	1.73	1.73
Standard deviation ($\boldsymbol{\beta_4}$)	*0.16*	*0.10*	*0.08*	*0.06*	*0.04*

There are two implications: the first is that even with an arbitrarily large number of observations, the researcher still underestimates differences across locations and overestimates catches in absolute terms. Due to selection these estimates are biased in any finite sample. The second, however, is that when the number of observations is small these estimates are *also* inaccurate, and it is more likely the researcher will incorrectly predict relatively unproductive locations to have larger catches than productive locations, which is exacerbated when locations are relatively similar to each other.

Notably, the estimates in our Monte Carlo experiments above exhibited an upwards bias in the marginal utility from catch, due to the large number of observations and relatively large differences in average catches across locations, but this does not represent a universal trend. If the average catch across locations is similar, and the researcher does not observe many samples, it is possible for the marginal utility from catches to be biased downwards.

1.6 EMPIRICAL EXAMPLE IN THE BERING SEA CATCHER VESSEL POLLOCK FISHERY

We demonstrate the importance of correcting for selection bias with an empirical example in the Bering Sea pollock fishery for the 2015 B-season. First, our sample contains 67 catcher vessels that deliver to the inshore processing sector, comprising approximately 45 percent of the total catch in a year (the total includes catcher vessels, catcher-processors, and motherships). These vessels exhibit considerable variance in the size (by gross tons), age, and horsepower across the fleet, as shown for the year 2015 in Table 1.8. For the purposes of estimation we will normalize vessel characteristic data such that the mean is one for each characteristic, and catch and distance are divided by one hundred (by rescaling the data we ensure they are of similar magnitude).

Table 1.8: Vessel characteristics in 2015 B-season

	Age (years)	**Horsepower**	**Gross tons**	**Catch per haul (metric tons)**
1st quantile	35.0	1260.0	192.0	61.2
Mean	36.9	1885.0	354.9	102.0
3rd quantile	39.0	2000.0	394.0	133.5

The choice set for the individual fisher is discretized into areas that are 1 decimal degrees east-west by 0.5 degrees north-south. These are the commonly used "Stat6" areas designated by the Alaska Department of Fish and Game (ADFG). A map of the areas visited by fishers in the B-season of 2015 is shown in Figure 1.7. We choose to examine the B-season specifically because the tradeoffs across locations (e.g. between catch and distance) are substantially different in the A-season when the presence of high-valued roe enters the choice calculus of the fisher and at which point vessels are also restricted by ice cover at different times.

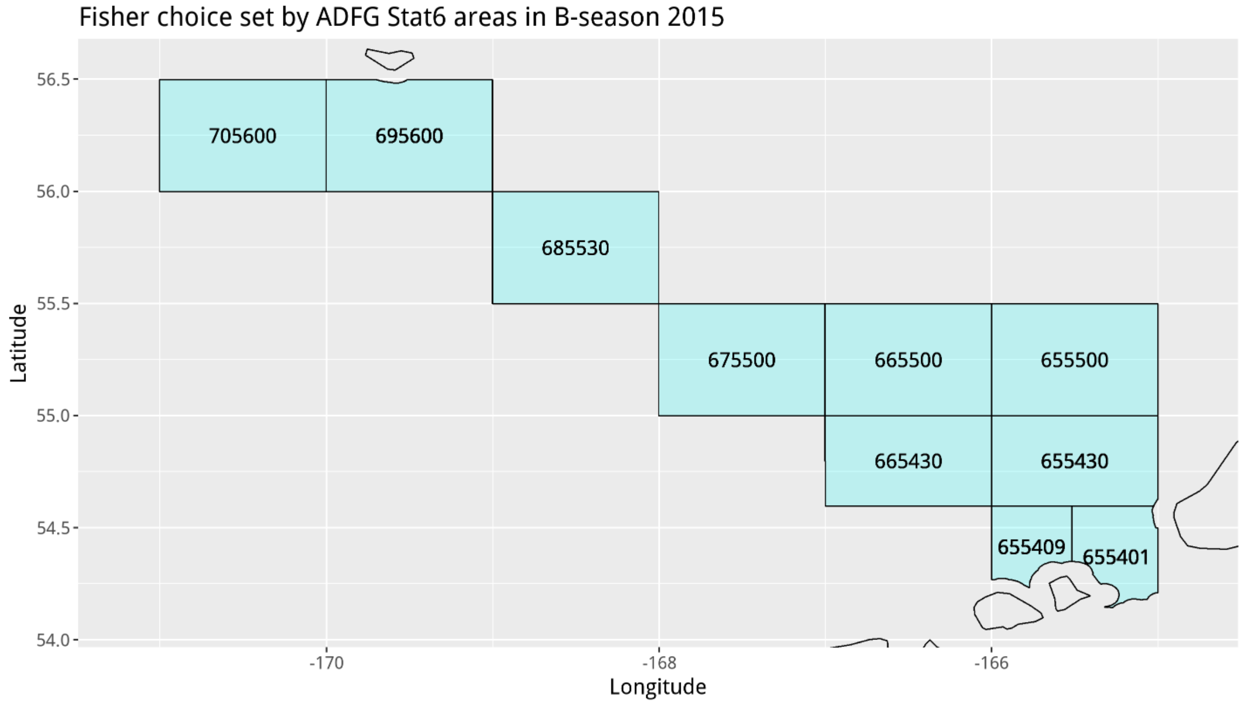

Figure 1.7: Fisher choice set Bering Sea pollock B-season 2015

For each haul, the researcher observes the vessel's starting location (the end point of the last haul), the vessel's characteristics, the location the vessel chooses, and the weight of the catch at the chosen location. Catcher vessels that operate in the Bering Sea pollock fishery tend to choose locations closer to Dutch Harbor and Akutan (the two ports they offload at). The sample size and average catch at each location with a minimum of 20 observations is shown in Table 1.9. Stat6 areas to the northwest generally have fewer observations and smaller average catches, but the researcher cannot ascertain if differences in catch are understated due to selection.

Table 1.9: Sample size and average catch by location

ADFG Stat6 area	Number of observations	Average catch (metric tons)
655401	39	107.20
655409	390	91.13
655430	852	101.30
655500	110	136.22
665430	117	116.41

665500	28	162.11
675500	92	99.64
685530	32	64.18
695600	23	84.29
705600	56	92.96

We use the correction function in a joint estimation methodology to ascertain if vessels tend to travel farther distances only when catches will be good in those locations. The catch equation we estimate is similar to Equation 1.1, except with vessel age interacted with vessel horsepower as the single covariate (Equation 1.16). Meanwhile, our cost equation (Equation 1.17) uses interactions of all vessel characteristics as well as a linear component on mileage.

Equation 1.16: Empirical example catch equation

$$Y_{itj} = \beta_j * (Age_i * Horsepower_i) + u_{itj}.$$

Equation 1.17: Empirical example cost function

$$C_{ijk} = \gamma_1 * (distance_{jk}) + \gamma_2 * (distance_{jk} * tons_i) + \gamma_3 * (distance_{jk} * hp_i) + \gamma_4 * (distance_{jk} * age_i) + \gamma_5 * (distance_{jk} * tons_i * hp_i) + \gamma_6 * (distance_{jk} * tons_i * age_i) + \gamma_7 * (distance_{jk} * hp_i * age_i).$$

Table 1.10: Discrete choice parameter estimates

	$\boldsymbol{\alpha}$	$\boldsymbol{\gamma_1}$	$\boldsymbol{\gamma_2}$	$\boldsymbol{\gamma_3}$	$\boldsymbol{\gamma_4}$	$\boldsymbol{\gamma_5}$	$\boldsymbol{\gamma_6}$	$\boldsymbol{\gamma_7}$	$\boldsymbol{\Sigma\gamma}$
FIML	13.30	-6.79	-3.51	10.60	1.77	-0.89	4.50	-8.74	-3.02
SE	*4.93*	*1.93*	*0.52*	*0.44*	*0.86*	*0.03*	*0.80*	*0.37*	*1.81*
Uncorrected	8.20	-7.45	-0.11	5.54	3.84	-0.27	0.26	-5.37	-3.56
SE	*0.59*	*1.39*	*1.87*	*2.75*	*1.27*	*0.17*	*2.11*	*2.78*	*10.94*

Recall that we have normalized vessel characteristics to unity, and therefore the marginal disutility of distance evaluated at the mean can be written as the sum of the cost function parameters. We find full-information estimation with the correction function estimates a larger marginal utility of catch, as well as a smaller marginal disutility of distance, and the disutility of distance is not significantly different from zero[15] when estimates are uncorrected (in Table 1.10).

As a result, tradeoffs between locations will be underestimated. These results are a consequence of larger predicted catches at locations that require larger travel costs, when we do not include a correction for selection, and the results are consistent with the smaller number of observations at locations that require traveling farther distances.

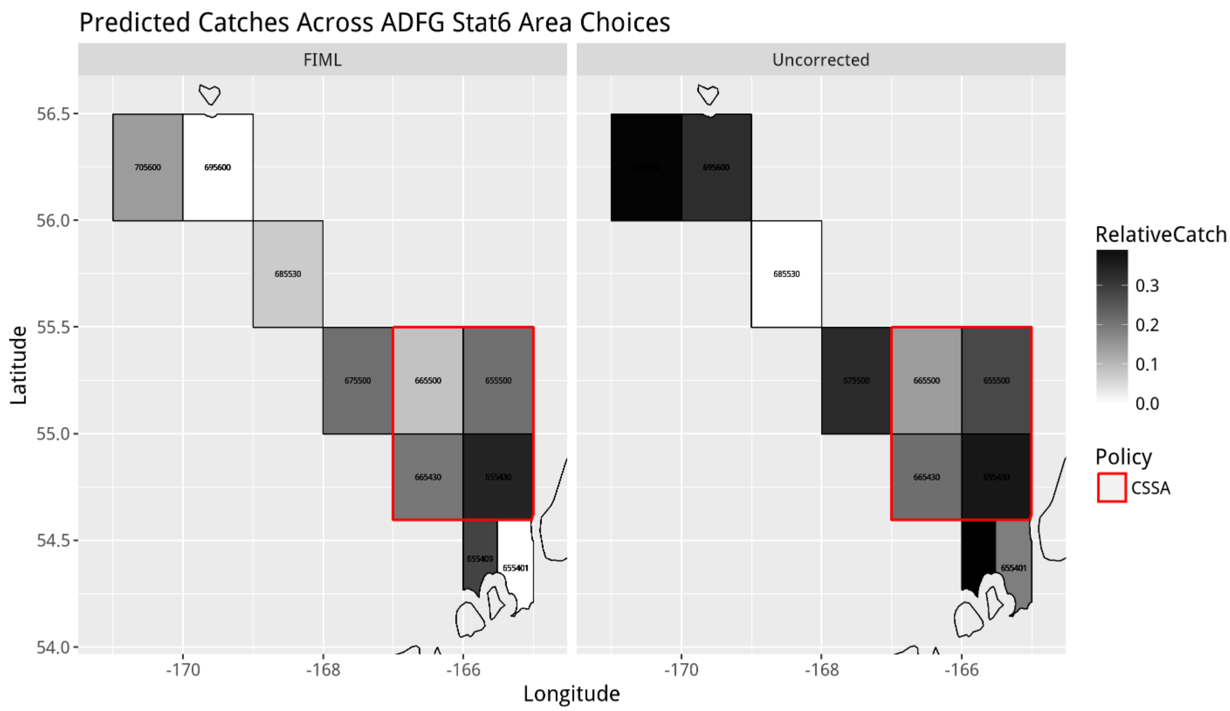

Figure 1.8: Predicted catches

Figure 1.8 illustrates that uncorrected predicted catches in locations not visited often in the northwest are relatively large (compared to the minimum predicted catch). Vessels are only willing to go to locations further away when catches are especially good[16], biasing predicted catches in those locations upwards. To show this, we can test whether our approximation of the conditional error is significantly different from zero, in Table 1.11.

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[15] The standard errors for the disutility of distance are calculated using the delta method.
[16] Or when catches are poor elsewhere.

Table 1.11: Model statistics

	AIC	**BIC**	**Predictive R^2**	**Log-likelihood**
FIML	-5058.76	-4408.89	0.72	2648.38
Uncorrected	-3490.05	-3446.36	0.73	1753.02
Likelihood ratio tests				
LR test (H0: uncorrected model; degrees of freedom = 111)	1790.72			
LR test (H0: joint estimation with no correction; dof = 100)	438.66			

Furthermore, a likelihood ratio test rejects the null (uncorrected) model. The full-information model also fits the data better according to Akaike and Bayesian information criterion. Interestingly, the predictive R^2 of both models are very similar, which implies a model with a high percentage of correct predictions can still provide inaccurate welfare impacts and incorrect predicted catches.

However, when we estimate a more parsimonious model with only one covariate in the cost function, for example if the data available to the researcher is sparse, the uncorrected model performs very poorly at predicting correct choices, while the full-information model still predicts a high percentage of correct choices. When relevant information is omitted or unavailable the correction function can help explain how unobserved variation impacts fisher choice, generating correct predictions. Uncorrected estimates of a misspecified model will compound the prediction error, and the errors in welfare estimates become larger.

Note that relative catches (compared to the minimum predicted catch) are larger in the northwest under the uncorrected model in Figure 1.8. In addition, Table 1.12 shows that *absolute* catches are predicted to be larger under the uncorrected model as well. These results overestimate the quantity of fish in the sea, along with misestimating welfare effects. Fishers and regulators often arrive at different conclusions as to the health of fishery stocks, and selection by the fisher can be one possible reason, as fishers tend to visit locations where fishing is good and catches are bountiful.

Table 1.12: Predicted catches

ADFG Stat6 area	FIML (metric tons/100)	Uncorrected (metric tons/100)
655401	0.43	0.79
655409	0.55	0.94
655430	0.58	0.92
655500	0.52	0.85
665430	0.52	0.81
665500	0.47	0.76
675500	0.52	0.89
685530	0.46	0.67
695600	0.43	0.89
705600	0.49	0.93

Finally, we can use the log-sum formula (Train 2009) to calculate percentage welfare changes from a hypothetical spatial closure. The enclosure in Figure 1.8 delineates the areas in the choice set that overlap with the Chinook Salmon Savings Area (CSSA) as defined by Amendment 58 (2000)[17]. The CSSA was closed in the B-season after September 15th if a fixed limit of Chinook salmon bycatch was attained. This regulation was subsequently removed in 2010 (Amendment 91). We show the potential welfare loss to the fleet from a hypothetical season-long reenactment of this closure in Figure 1.9, faceted by vessel horsepower.

[17] The Chinook Savings Area actually extends an additional 0.10 decimal degrees south into Stat6 areas 655409 and 655401; however, for the purposes of this hypothetical illustration we only examine closing intact Stat6 areas. A more accurate methodology would require manually discretizing locations, and not according to existing ADFG maps. Also note that the CSSA is larger than the shown enclosure, which only represents the areas in the choice set that overlap with the CSSA.

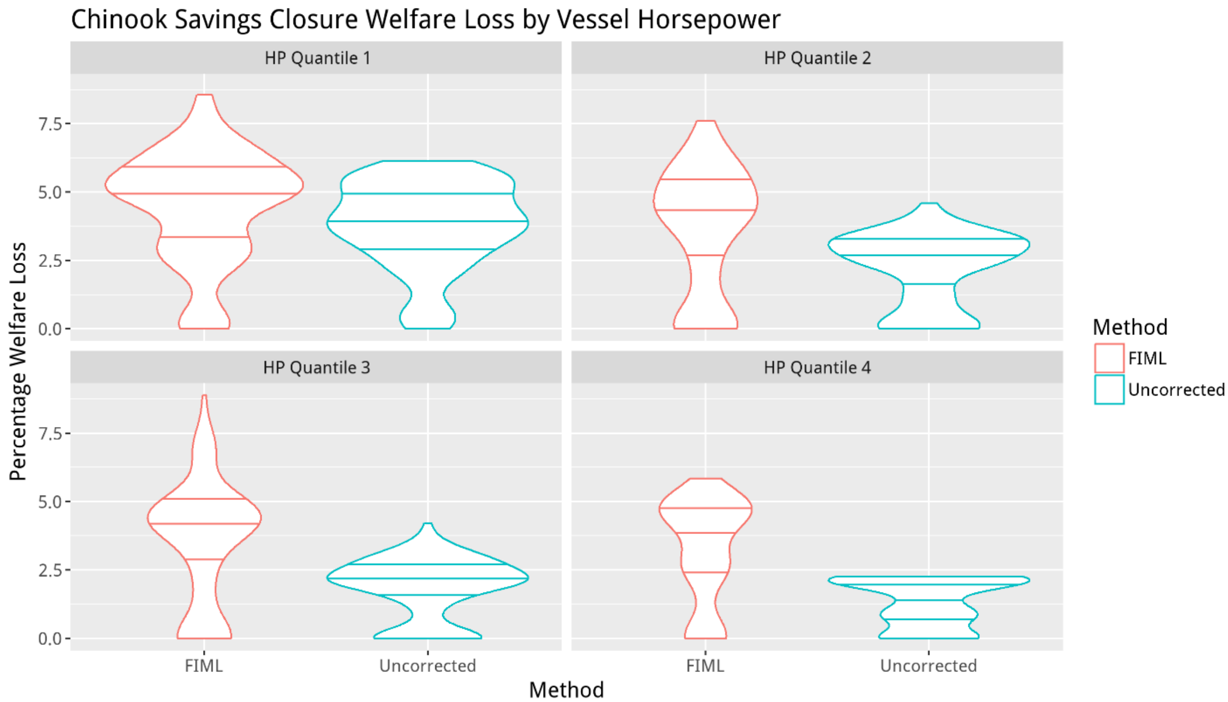

Figure 1.9: Welfare loss from hypothetical spatial closure

Note that percentage welfare losses are higher under full-information estimation that the uncorrected model. The median welfare loss when selection is corrected is roughly equivalent to the 75th percentile of uncorrected estimates for the smallest horsepower quantile, while the difference increases as horsepower increases. In addition, we note that absolute welfare losses tend to decrease as vessel horsepower increases, consistent with previous findings (Haynie & Layton 2010).

Because catches outside the spatial closure are predicted to be larger under the uncorrected model, the impact of the Chinook salmon savings area is underestimated. In reality, locations infrequently visited exhibit an upwards bias in predicted catch, as vessels only tend to visit those locations when fishing is good. The researcher would incorrectly believe the next-best options for fishers are relatively similar to catches within the closure, and therefore inaccurately estimate smaller forgone benefits.

1.7 DISCUSSION

This chapter illustrates how private information available to the fisher and not known to the researcher is not accounted for in catch expectation proxies created by the researcher. Because fishers are more likely to choose locations with larger catches, researchers are also more likely to observe large, positive catch deviations. An empirical example in the Bering Sea pollock fishery shows that fishers only visit locations farther away when catches are relatively good, which underestimates the welfare impacts from a hypothetical spatial closure.

We suggest an extension to the work of Dahl (2002) by jointly estimating the corrected catch equation with the polychotomous discrete choice problem, in order to correct the selection bias that occurs in catch expectation proxies due to non-randomly sampled data. Using a Monte Carlo experiment, we show how full information likelihood estimation can purge the bias from predictions of catch, which allows the researcher to correctly infer how fishers trade off expected revenues and costs.

Our methods explicitly acknowledge that the fisher has information not known to the researcher when the fisher makes a decision where to fish, and the sample of catches the researcher uses to construct catch expectation proxies is selected by the fisher with the intention of increasing their catch and maximizing their utility. This can occur when the availability of fish varies over time: for example, a skillful captain may be able successfully follow an agglomeration of fish across space. Then, the researcher would tend to observe catches at certain locations when the fishing is good.

Incorrectly predicting the spatial opportunities for fishing implies researchers will underestimate the welfare effects from policies such as spatial closures. When relative differences across locations are underestimated, a researcher would inaccurately believe the next-best options for fishers are close substitutes. In reality, the researcher cannot observe catches at locations the fisher does not choose, and the fisher only chooses infrequently visited locations when they have private information the catches will be large there.

These methods may be extended to any polychotomous choice problem that requires constructing proxies for unobserved alternatives, and are relevant to the broader literature examining self-selected data, e.g. examining how migration flows are affected by expected wages across countries. We note that the results we present are a function of the data and fishery we choose to investigate. We show that the precise nature and sign of the bias will depend on the true data-generating process, and if no bias exists, the polynomial terms can be jointly tested under the null that the expected conditional error is equal to zero.

Finally, this chapter uses a relatively stylized model that does not account for state dependence or dynamic decision-making, and treats all hauls within one season of fishing as coming from the same choice set. An avenue for future work is to examine how the correction function works with more robust constructions of expected catch, such as weighted averages that use historical catches of different time series lengths and spatial sizes. Because the polynomial function used to approximate the conditional error is straightforward to add to any linear relationship, and can be used to test whether selection actually occurs in a given set of data, the methods outlined here are relevant to a large number of fisheries and econometric problems. Models that do not test and correct for selection bias risk incorrectly inferring how fishers make tradeoffs between catches and costs, and underestimating the impacts from spatial policies that affect the fisher's choice set.

Chapter 2. AN EMPIRICAL EXAMINATION OF SIZE-TARGETING IN THE BERING SEA POLLOCK CATCHER PROCESSOR FISHERY

Traditional weight-based fisheries quota management assumes that a single, 1-kilogram fish is equivalent to two 500 gram fish. However, both biologically and economically, this is rarely true. In order to ascertain how a change in the average size of fish caught by harvesters affects the total value of an important fishery, we investigate the catcher processor sector of U.S. Bering Sea pollock fishery ("pollock fishery"), by examining the production relationships between different fishery products and the size of fish.

Larger pollock in the pollock fishery can be more valuable per unit weight because larger fish may be transformed into more valuable products and have higher product recovery rates. For example, the production equipment for producing certain types of fillet require a minimum size for processing, and production equipment may vary across vessels.[18] In addition, vessels may face different demand for their products, as vessels participate in various markets with unique buyers, and vessel-specific demand may depend on vessel-specific production characteristics and product quality.

We find that as harvesters catch smaller fish, they substitute from higher-valued fillet products to typically lower-valued surimi. While other studies have looked at the production relationships of alternate fishery product forms (Asche et al. 2002; Morrison-Paul et al. 2009), or if size matters across different fisheries (Sjoberg 2015, Asche et al. 2015), we explicitly link changes in size with choice of product mix, and identify how this response varies within a fishery as well.

We apply a flexible, data-determined estimation technique to control for latent heterogeneity across harvesters in their sensitivity to size of fish (Lin et al. 2012; Pesaran et al. 2008). This

[18] As one example, the minimum size for the BAADER 212 Heading, Gutting and Filleting Machine is 400g for pollock. In addition, vessels can run more product per day through the plant when producing fillets, increasing their total production with bigger fish.

algorithm arrives at harvester groupings by repeatedly estimating the revenue-size relationship, learning and improving fit each time, and letting the data determine outcomes while making no a priori assumptions on what kind of harvesters prefer larger fish.

First, we find that harvesters can mitigate losses in revenue due to changes in fish size by employing different strategies. Production technology enables them to produce fillets even when fish are small, or market access can ensure relatively higher prices for surimi even if they substitute across products. It is unlikely we would assume these strategies had we made a priori groupings (for example, based on vessel-specific historical product choice or product prices). Second, the harvesters that are not sensitive to changes in fish size can impose a negative externality on other members of the fleet that are sensitive to changes in fish size.

This negative externality occurs because searching for larger fish, instead of targeting smaller fish that are readily available, can be costly if harvesters must expend more days fishing, spending more fuel and traveling farther distances. Because the total allowable catch (TAC) in the pollock fishery is not managed by fish size, a non-cooperative harvester can decrease their costs by targeting younger, smaller fish, if they are willing to forgo the marginal increase in revenue from substitution to more valuable product forms. Therefore, a harvester whose revenue is not greatly impacted by changes in fish size actually finds the tradeoff to target smaller fish more palatable, and harvesters are not equally responsible for the negative externality.

The pollock fishery is a high-volume fishery, characterized by large recruitment classes whose occurrence is only weakly related to the current spawning biomass.[19] Because of this, we focus here on only on the primary biological difference between larger and smaller pollock, the rate of growth.[20] Targeting smaller fish negatively affects the value of the fishery by decreasing the rate of growth of the biomass on average, because smaller pollock tend to be younger pollock, which

[19] For example, see Figure 1.36 (Ianelli et al. 2015) in the pollock assessment. The authors describe the stock-recruitment relationship as displaying “a fair amount of variability both in the estimated recruitments and in the uncertainty of the curve”. Other ecosystem factors such as ocean temperatures, cannibalism, (Wespestad et al. 2000) and euphausiid abundance may be important determinants of pollock recruitment (Coyle et al. 2011).

[20] This is in contrast with other fisheries, where there may be a greater impact from the fecundity of larger fish, or in fisheries concerned with hereditary effects from selection; the value we find from leaving small fish to grow is a function of the specific biological characteristics we model from the pollock fishery.

grow at a faster rate. By filling quotas with a greater quantity of young, fast-growing pollock the overall rate of growth for the population decreases. Each individual non-cooperative harvester does not have the incentive to take this effect into account, in essence racing to fish for smaller fish (Diekert 2010).

Here we first investigate how fish size affects harvester revenue by examining the relationship between fish size and product choice, estimating a system of revenue share equations for the pollock fishery. We allow the impact from size to be heterogeneous across vessels, without making a priori assumptions about a vessel's group membership, or the extent of the heterogeneity. We find that while certain vessel groupings are responsive to size, other vessels never substitute across products. In addition, if we assume parameter homogeneity and pool all vessels for estimation, we run the risk of overestimating the importance of size for some vessels, while not adequately capturing how other harvesters substitute across products.

Additionally, we use a dynamic age-structured model to illustrate how vessel groupings with weaker incentives to target larger fish may instead choose to decrease their harvesting costs. Because we identify the heterogeneous relationships between revenue and fish size from our production model, we can accurately capture welfare impacts because the harvesters with weak revenue-size relationships are expected to catch smaller fish. We show that the benefits to targeting larger fish extend past higher prices and transformation to more valuable products. Approximately 75-85 percent of increases in revenue can be explained by increased future quotas, due to increasing the biomass rate of growth. Because harvesters do not internalize the future growth in biomass, we find that heterogeneity in the pollock fishery exacerbates the growth externality because certain harvesters prefer catching small fish that grow at a fast rate. We find potential increases in profit by more than 10 percent in a year, but collective action is hindered by heterogeneous preferences, and ignoring these vessel differences would underestimate the impact of size targeting in the pollock fishery.

2.1 Fishery setting: the U.S. Bering Sea pollock catcher processor fishery

The U.S. Bering Sea pollock fishery is among the largest in the world by volume, and the catcher-processors in our sample account for an average of approximately 520,000 metric tons of fish worth 610 million dollars (first wholesale post-production, 2003-2013, in 2013 dollars). [21] A catcher-processor transforms fish into a variety of products on board the vessel. We look at 4 types of products: roe, surimi, fillet, and other. The "other" category comprises a wide variety of products, such as stomachs and milt, but ranked by revenue is primarily fish meal, whole fish, and "headed and gutted".

A single fish is not transformed into a single product, but various parts of the pollock are transformed into one or more products. However, factors such as the size of fish and production technology dictate which products are made. Certain products are more valuable and the total quantity of product that can be recovered depends on the interaction between product choice and fish size. When production equipment and capital characteristics vary across pollock catcher-processors this impacts the production strategies we observe.

Although the production technology and capital characteristics of vessels are not malleable in the short run, certain vessels have undergone refittings. Refitting and conversion of a catcher-processor is costly, and requires forgoing harvest for at least one season[22]. Because our estimation allows for the response from size to vary across vessels, but not across time, each vessel must maintain the same production and capital characteristics across their set of observations to be considered the same vessel. Therefore, we treat catcher-processors that underwent conversions as distinct vessels in our panel. In this manner, if more productive vessels (in terms of revenue) desire

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[21] Our sample excludes motherships, and one Amendment 80 catcher-processor that primarily used non-pelagic trawl (the gear of our sample is pelagic trawl only). In addition, there is one omitted catcher-processor that refit to only produce headed and gutted products; because this vessel is always placed by itself in its own group, it is not included due to confidentiality. Note the total catch reported here is therefore slightly smaller than other published figures, and does include community development quota.

[22] Because vessels must forgo a lengthy period of fishing, usually spanning at least one season, we can identify when vessels underwent refitting and conversion, and cross-check by personal conversation and with the vessel owner's public website.

certain sizes or consistency of size in a haul, identification is still obtained as long as the factors affecting both revenue and choice of size do not change over time for a single harvester.

We use vessel-specific data from 2003 to 2013 to create an unbalanced panel of 17 individuals. Using the weight produced of specific types of products, and the price per weight the individual vessel receives for that product, we can create revenue shares for each product, for each individual. Production data are from weekly production reports to the National Marine Fisheries Service, augmented by the Alaska Fisheries Information Network with price data from the Alaska Department of Fish and Game's Commercial Operators Annual Report (COAR) data collection program. Because production data is only reported weekly before 2009[23], we aggregate haul-level data to obtain catch composition observations by week, and match characteristics of pollock catch to corresponding weekly production composition. Catch composition data is from the North Pacific Groundfish Observer program, which records for each individual haul, the weight caught, duration of haul, mean weight, as well as variance of weight in haul. Mean weight in haul as well as variance of weight in haul are ascertained from random sampling of fish in hauls, when observers measure and weigh individual fish (Ianelli et al. 2016).[24]

Because the sizes and abundance of available fish, variances in size of available fish, and relative product prices all change over time, we observe vessels producing different products both within and across years. Vessels usually make contracts that fix the prices that they will receive before the season begins, based on their expectations from past survey and fishing years. We hypothesize that product choice will vary across years depending on the size of fish available to harvesters in that year, as harvesters have information about which age class is predominant in a year (and therefore if fish will be larger or smaller on average). In addition, as they encounter larger or smaller fish in a year, they may substitute production based on the biological characteristics of individual hauls. For example, even though fillet generally is more valuable per metric ton than surimi, production choices will depend on the sizes of fish encountered, as well as each vessel's underlying production technology.

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[23] Daily observations of production data are available since 2009. Results using daily observations are not qualitatively different in comparisons using daily versus weekly observations for the period 2009-2013.
[24] See Table 1.11 in Ianelli et al. (2016) for the numbers of fishery samples measured for length-weight by year.

For each product category, prices per metric ton of product vary across year and vessel, and vessels may receive different prices for their products because of the quality of their products or heterogeneous market access. Table 2.1 displays the average product price per metric ton of processed product, which is highest for roe, followed by fillet, surimi, and other.

Table 2.1: Price per metric ton of production by product type (2003-2013, 2013 USD)[25]

	1st Quartile	**Mean**	**3rd Quartile**
Fillet	$3,095	$3,479	$3,856
Other	$1,360	$1,665	$1,887
Roe	$9,602	$12,735	$16,213
Surimi	$2,070	$2,820	$3,425

In addition, vessels may choose to transform raw fish into different products throughout the year as they encounter larger or smaller sized fish, and vessels may produce more or less of certain products, as a result of the product prices they receive and onboard processing technology, as Table 2.2 shows below. Because catch and production do not always align exactly across time (fish caught today may be processed tomorrow or the day after), we manually smooth some observations over time to better match catch and production (for example if a vessel produces more product by weight than it caught, a physical impossibility).

Table 2.2: Proportion of production by product type (2003-2013)

	1st Quartile (Metric tons of product/Total production quantity)	**Mean (Metric tons of product/Total production quantity)**	**3rd Quartile (Metric tons of product/Total production quantity)**
Fillet	0.34	0.43	0.51
Other	0.13	0.20	0.28
Roe	0.01	0.05	0.11
Surimi	0.21	0.32	0.42

[25] Note that multiple products are made from a haul of fish and have different costs, so these prices do not capture the net revenue per ton of fish harvested.

The size of fish observed in fishery hauls varies over time for a number of reasons. The abundance, concentration, and location of larger fish vary from year to year. When larger fish are more difficult and more costly to target, vessels may not find it worthwhile to target them. Certain vessels may also tend to target and catch larger fish based on their processing equipment. The size of fish vessels encounter during the year also varies. One primary driver of the availability of larger-sized fish in the pollock fishery is the proportion of ages that comprise the biomass, which in turn depends on the recruitment to the fishery each year.

Recruitment in the pollock fishery is characterized by extremely large, seemingly stochastic year classes. Because these cohorts then comprise a large proportion of targetable biomass available to the fishery for several years, it can be costly not to fish on those large year classes when they enter the fishery. For example, when younger fish comprise a large proportion of the biomass, we would expect the average weight of fish caught to decrease, as younger fish are smaller. Figure 2.1 illustrates that the large recruit class of 2009, a recruitment of approximately 56 billion fish, first entered the fishery at age 3 in 2011, and proceeded to comprise a large proportion of catch in 2012 and 2013. As harvesters encountered more small fish, because younger fish comprised a large proportion of available biomass, the average size of fish they caught also decreased commensurately.

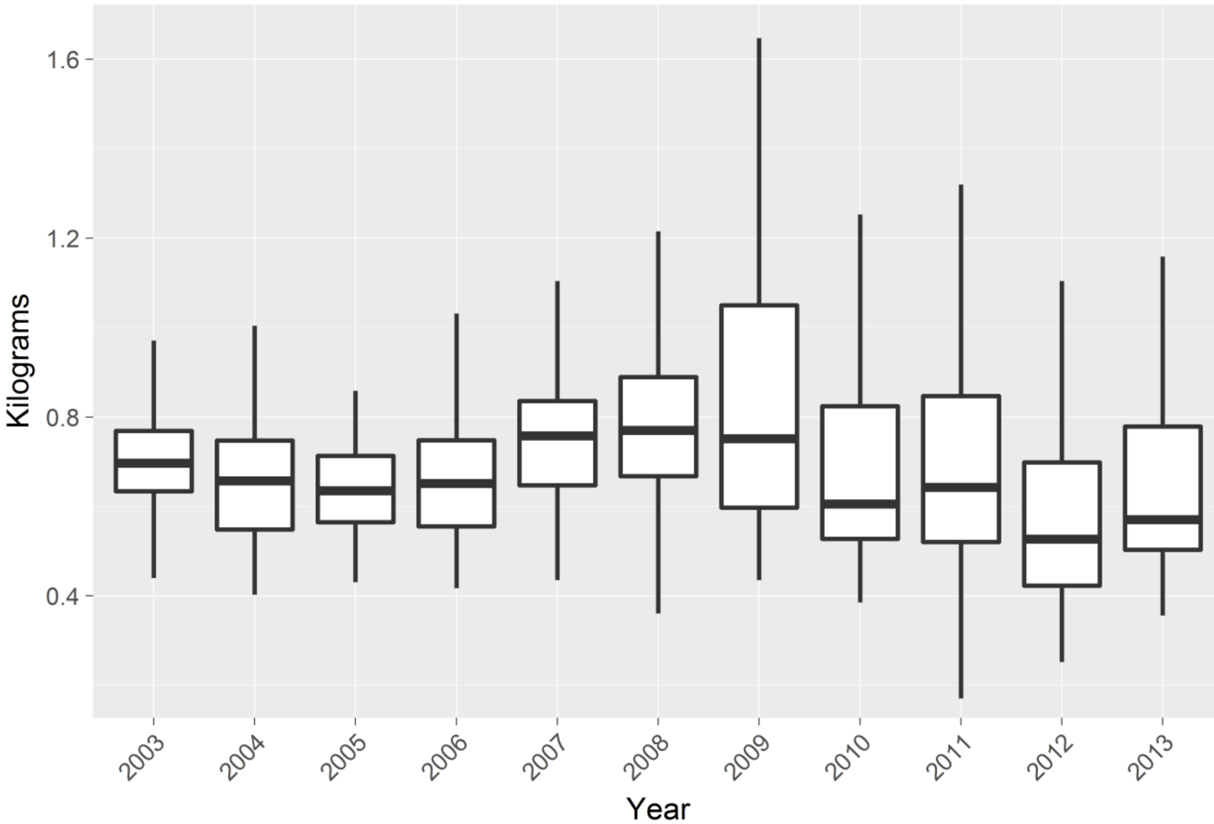

Figure 2.1: Mean size of fish caught by year

2.2 EMPIRICAL MODEL LINKING FISH SIZE AND HARVESTER PRODUCTION

We investigate whether harvesters can substitute to more valuable product forms when they catch larger fish. If so, the size of available pollock will impact overall fishery value. To capture patterns of substitution and how fish size impacts revenue, we use a structural production model, from a translog revenue function commonly seen in the fisheries production literature (for example see Asche and Hannesson 2002). A model with a flexible revenue function allows for interactions among the products (outputs) and inputs used for production, and we denote prices of products p_j and production inputs v_m. In addition, as production inputs in our flexible revenue function, we include expected biological conditions such as size of fish, the variance of the size of fish in haul, catch per unit effort, and product seasonality, all of which affect the relationships between inputs and outputs for pollock production (Morrison-Paul et al. 2009).

In the pollock fishery there is a winter A-season and a summer B-season. We assume seasonality enters the production function linearly, so that average revenue shares differ by season, due to the ability to produce a high-valued product, roe, in the A-season.[26] Roe is significantly more valuable per metric ton, and may also affect flesh quality and therefore the ability to produce other products. As roe occurs at a particular time, the extent of substitution with other products is minimal, but is an important factor in harvester decision-making in the A-season. To identify how production relationships change during these two seasons, we include a seasonal dummy variable.

The logged revenue for the i^{th} harvester in time period t is therefore a function of a vector of logged prices $\ln(p_{i,t,j})$ for each j^{th} product, and a vector of m logged biological characteristics of the catch $\ln(v_{i,t,m})$. Each product price and biological covariate is then allowed to interact with the others, where we estimate the free parameters $\alpha_j, \beta_{j,k}, \gamma_m, \delta_{m,l}, \theta_{j,m}$.[27]

Equation 2.1: Translog revenue function

$$\log(\text{Revenue})_{i,t} = c_r + \Sigma_j(\alpha_j)\ln(p_{i,t,j}) + (½)\Sigma_j\Sigma_k\beta_{j,k}\ln(p_{i,t,j})\ln(p_{i,t,k}) +$$
$$\Sigma_m(\gamma_m)\ln(v_{i,t,m}) + (½)\Sigma_m\Sigma_l\delta_{m,l}\ln(v_{i,t,m})\ln(v_{i,t,l}) + \Sigma_j\Sigma_m\theta_{j,m}\ln(p_{i,t,j})\ln(v_{i,t,m}).$$

Partial differentiation of the logged revenue equation with respect to each j^{th} logged product price gives us a system of j product revenue shares through application of the envelope theorem, from which these homogeneity and symmetry constraints follow:

Equation 2.2: Homogeneity and symmetry constraints

$$\Sigma_j\alpha_j = 1,\ \Sigma_j\theta_{j,m} = 0,\ \Sigma_j\beta_{j,k} = 0,$$
$$\Sigma_m\theta_{j,m} = 0,\ \Sigma_k\beta_{j,k} = 0,$$
$$\beta_{j,k} = \beta_{k,j},\ \delta_{m,l} = \delta_{l,m}.$$

[26] Roe is also produced in the B-season, but to a much lesser extent.
[27] Note that the constant c_r in the logged revenue function is not included in estimation of the revenue share functions as the revenue shares are derived from partial differentiation of the logged revenue function.

By estimating the sensitivity of the revenue share of each product type to fish size, we can estimate our coefficient of interest $\theta_{j,Z}$, denoting the effect that variation in size has on each product's share of revenue, conditional on product prices and other production inputs relevant to the harvester's decision of product mix. Each i^{th} catcher-processor's revenue share from the j^{th} product, from differentiation of the revenue function, is written as

Equation 2.3: Revenue share equation

$$s_{i,t,j} = \alpha_j + \Sigma_k \beta_{j,k} \ln(p_{i,t,k}) + \Sigma_m \theta_{j,m} \ln(v_{i,t,m})$$
$$= \alpha_j + \theta_{j,Z} \ln(Z_{i,t}) + \Sigma_k \beta_{j,k} \ln(p_{i,t,k}) + \Sigma_m \theta_{j,m} \ln(v_{i,t,m})\,;\; m \neq Z.$$

2.2.1 *Identification*

As prices and the biological characteristics of catch change, certain product forms will comprise a larger share of a harvester's revenue. For example, if harvesters can process greater quantities of fillet at higher prices when they encounter larger fish, fillet will become a more important component of their total revenue. We use these relationships to first capture the latent heterogeneity in substitution patterns across vessels, and then use the groupings we find to accurately estimate how revenue per unit of quota is affected by size.

Because vessels that are more technically efficient at producing certain products may desire certain sizes or variances of size in haul, they will receive a greater output of those products for the same level of biological input. As described by Hoch (1962), profit maximization implies they will also choose greater levels of that input. A solution to this simultaneity bias is to assume that the equilibrium values of the fish size input, for each harvester, are not exogenous, but rather a function of a time-invariant harvester-specific technological parameter that also affects the harvester's revenue share.

Our model assumes that factors affecting the revenue and choice of size by the harvester may be different for each harvester, but this factor does not change over time for them. We do not include year fixed effects, but we do include variables that would conceivably affect both product choice and fish size over time, such as changes in deflated product prices. Notably, product-specific prices from the COAR data are constant within a year for a given vessel, although the revenue per metric ton of catch varies as the product mix changes within a year.

Then, $\alpha_{i,j}$ reflects differences in technical efficiency across vessels, and differences between vessels affecting both revenue share and observed size of fish caught are accounted for:

Equation 2.4: Revenue share equation with vessel fixed effect

$$s_{i,g,t,j} = \alpha_{i,j} + \theta_{g,j,Z} \ln(Z_{i,t}) + \Sigma_k \beta_{g,j,k} \ln(p_{i,t,k}) + \Sigma_m \theta_{g,j,m} \ln(v_{i,t,m}) + \mu_{i,t,j}.$$

Because we are investigating the existence and extent of group heterogeneity, and the differing impacts from variation in size, we let $\theta_{j,Z}$ vary among an unknown number of groups so that the effect is potentially different for each group, and group membership of the i^{th} harvester is not known. Other parameters can also be heterogeneous, but we allow the distribution of these parameters to be disperse within each group (estimating average effects),[28] as we are interested in which harvesters have similar fish size preferences and how that affects the value of the fishery.

The i^{th} harvester is a member of group g ($\{g...G\}$), where G is the unknown total number of groups. Each harvester may only be a member of a single group and $\mu_{i,t}$ is an idiosyncratic error. Depending on their group membership, a harvester may or may not be responsive to changes in fish size, although we do not place a priori restrictions on a) how many groups there are, or how many heterogeneous slope parameters exist in the fleet, and b) which vessels are in which groups.

Estimation of latent group structures and parameter homogeneity in panel data is a rich literature, with a variety of methodologies proposed recently. In the fisheries literature, an example is found in Felthoven et al. (2009), who use a latent stochastic production frontier model to estimate heterogeneity in production capacity. The methodology we use, suggested by Lin and Ng (2012),

[28] The implication is that individuals will have similar fish size preferences in each group, but other covariates are allowed to be disperse, and we estimate the average effect of these parameters across the vessels in a group.

is intuitively similar to the k-means clustering algorithm (Hartigan 1975), is based on hypothesis testing, and straightforward to extend to a seemingly unrelated regressions (SUR) framework.

We estimate the system of equations using SUR, thus allowing for cross-equation constraints, using the following algorithm suggested by Lin et al. (2012) to determine group membership in our system of equations:

1) Let the number of groups $g = 1$.
2) Find the fixed effects estimator for all *j* products.
3) Use the parameter homogeneity test (Pesaran and Yamagata 2008) under the null hypothesis of parameter homogeneity. If homogeneity is rejected, repeat steps 4-8 for *g=2:N*.
4) Randomly assign individuals into groups *1:g*.
5) For each group, find the fixed effects estimator all *j* products, allowing for cross-equation correlations.[29]
6) Calculate a test statistic TS_i^g for each *i* harvester for all g groups. Move the i^{th} harvester to group $\hat{g}$ where $\hat{g}$ is given by $\min\{TS_i^g\}$.[30]
7) Repeat steps 5 and 6 until no individual changes groups.
8) Use the parameter homogeneity test under the null hypothesis of parameter homogeneity. If subsample homogeneity is rejected, repeat steps 4-8 for the next g. Otherwise, break.

We first determine if parameter heterogeneity is reasonable. Then, for a given number of groups, we determine individual harvester group membership. The number of groups is then determined by iteratively testing for subsample parameter homogeneity. Pesaran et al. (2008) show that the parameter homogeneity test is consistent as $\sqrt{N}/T^2 \to 0$, while Lin et al. (2012) use Monte Carlo simulations to show that for single-equation estimation the k-means algorithm in conjunction with a parameter homogeneity test can consistently estimate the true number of groups even for small

[29] Correlations are allowed to vary across groups.

[30] For example, in the single-equation (single product) case Lin et al. (2012) use $SSR_i^g = \sum_{t=1}^{T}\left(s_{i,t,j} - \alpha_j - \hat{\theta}_{g,j,Z}\ln(Z_{i,t}) - \Sigma_k\hat{\beta}_{j,k}\ln(p_{i,t,k}) - \Sigma_m\hat{\theta}_{j,m}\ln(v_{i,t,m})\right)^2$ where $\hat{\theta}_{g,j,Z}, \hat{\beta}_{j,k}$, and $\hat{\theta}_{j,m}$ are the estimates from step 5, and sum of squared residuals are for the i^{th} harvester only.

sample sizes. In particular, they find larger T decreases root mean squared error more than larger N, and the method has good finite sample properties for a population of small N, large T, similar to our population.[31]

For the parameter homogeneity test of Pesaran et al. (2008), we compare the slope estimates of the individuals to a suitable group estimator. The null hypothesis of the test can be written as $H_0\colon\ \theta_{i,Z} = \theta_Z\ \forall\ i$. The notation $\theta_{i,Z}$ denotes a vector of coefficients associated with covariates Z from the i^{th} harvester we wish to jointly test, such that θ_Z is a suitable pooled estimator of the coefficients. The test is based on the dispersion of the individual i slope estimates from a suitable pooled estimator, and Pesaran et al. show in the single-equation case the suitable pooled estimator is the weighted fixed effects estimator (Swamy 1970).

For the test statistic that identifies group membership in step 6), we use the *individual's* dispersion statistic $\frac{S_i - k}{\sqrt{2k}}$, where k is the number of parameters and S_i tests the difference between an individual's parameter estimate compared with each group parameter estimate. This allows us to cluster vessels based on how similar the estimates of their size coefficients are. [32]

We jointly test our coefficients of interest, the effect of size on each revenue share $\hat{\theta}_{i,Z}$, against the weighted fixed effects SUR estimator $\widehat{\theta}_{WFE,Z}$. Because we simultaneously estimate three revenue share equations, in contrast to the single-equation test statistic, we modify the test statistic to take advantage of the cross-equation correlations, using the pooled error covariances estimated from ordinary least squares residuals. The test is performed for all revenue share equations simultaneously, by stacking the revenue share equations and partitioning the size covariates in the stacked model, applying the Frisch-Waugh-Lovell Theorem (Greene 2008). Details on the

[31] Lin and Ng (2012) show that an increase in T decreases estimation error more than an increase in N. Furthermore, in their Monte Carlo experiments root mean squared error appears convex in T, performing well at T=200 (the largest T attempted in their experiments). The average number of observations per individual in our panel is approximately 170.

[32] We use the individual dispersion statistic instead of the sum of squared residuals for two reasons: because we find this method to be more robust to the initial starting conditions of the algorithm, and this method groups vessels based on how similar their size coefficients are. The formula for the statistic can be found in the Appendix and Pesaran et al. 2008. When we use the sum of squared residuals, the algorithm sometimes does not converge for the presented number of groups when we increase the number of initial starting conditions.

modified test statistic, as well as Monte Carlo experiments showing the efficacy of the algorithm and accuracy of the modified test for a SUR system of equations, can be found in the appendix.

2.2.2 *Empirical results*

For each of the four product revenue share regressions (Fillet, Surimi, Roe, and Other) we allow the size-response parameter to be estimated heterogeneously, while including vessel fixed effects and a season dummy for each regression. Because the revenue shares sum to one, we drop the Roe equation, although the coefficients can be recovered through our homogeneity and symmetry coefficient constraints. Because the k-means algorithm is sensitive to the initial starting point, we rerun the initial group assignment for each number of groups multiple times.[33] Then, to ensure that we find a global minimum, we use the initial group assignment that results in the smallest test statistic summed across group. Each group contains at least 3 vessels, which protects confidentiality.[34]

When the number of groups is 3 or less, we reject the null that there exists subsample parameter heterogeneity. Therefore, in each instance we increase the number of groups and re-estimate the fixed effects estimator, allowing vessels to move between groups in each new iteration.

When the number of groups is equal to 4, we fail to reject the null for all 4 subgroups after placing individuals in their best fit groups, and signifying there are five groups whose members are not significantly different from each other. The fixed effects estimates and test values are given below, where the parameter homogeneity test is asymptotically distributed standard normal. For certain vessel groupings, size has a significant effect on the revenue share from fillet or surimi, while other vessels maintain the same product revenue share regardless of size. We highlight select coefficients in Table 2.3, the responsiveness from changes in fish size, but all parameter estimates are found in the Appendix. Own-product-price coefficients are generally positive, and other-

[33] Lin et al. also rerun the algorithm with multiple initial group assignments, but the optimal number of initial seeds is unclear. We experimented with increasing and decreasing the number of initial group assignments, and found no difference in increasing the number of initial seeds from 30 to 60. We choose to run the algorithm with 60 initial seeds for all group sizes.

[34] Our results are robust to this constraint – when we run the algorithm without the constraint, we derive a final grouping with at least 3 vessels per group organically.

product-price coefficients generally negative, as economic intuition would suggest, although Fillet and Other are sometimes complements or not significantly different from zero.

Table 2.3: Estimation with 4 groups fit by k-means algorithm

G=4	***Group 1***		***Group 2***		***Group 3***	
	Beta	*SE*	*Beta*	*SE*	*Beta*	*SE*
Fillet WPF	0.049*	0.013	0.134*	0.017	0.086*	0.009
Other WPF	0.003	0.006	0.002	0.008	-0.035*	0.006
Surimi WPF	-0.030*	0.007	-0.149*	0.017	-0.102*	0.011
Dispersion test	1.159		1.058		0.879	
R^2	0.999		0.999		0.999	
*N*T*	565		658		1286	
	Group 4		***Pooled estimation***			
	Beta	*SE*	*Beta*	*SE*		
Fillet WPF	0.027	0.016	0.096*	0.007		
Other WPF	-0.008	0.006	-0.014*	0.004		
Surimi WPF	-0.026*	0.012	-0.070*	0.006		
Dispersion test	0.672		10.488			
R^2	0.999		0.999			
*N*T*	542					

If we assumed parameter homogeneity and pooled all vessels for estimation, we would overestimate the importance of size for some vessels that never substitute across product types, while not adequately capturing how other harvesters substitute across products.

We highlight two primary results. First, even when size responsiveness is allowed to be heterogeneous, size generally has a positive impact on fillet revenue share and a negative impact on surimi revenue share for all 4 groups (size does not have a significant effect on fillet revenue share for Group 4). Harvesters generally prefer larger fish because they can increase their revenue share of higher-valued fillet by substituting away from lower-valued surimi (Figure 2.2), with an average 7.4 percentage point increase in fillet revenue share, and 7.6 percentage point decrease in surimi revenue share. The exceptions are Groups 1 and 4, which both produce a relatively constant proportion of fillet revenue share. Interestingly they consistently produce a large share of fillet, rather than always producing surimi.

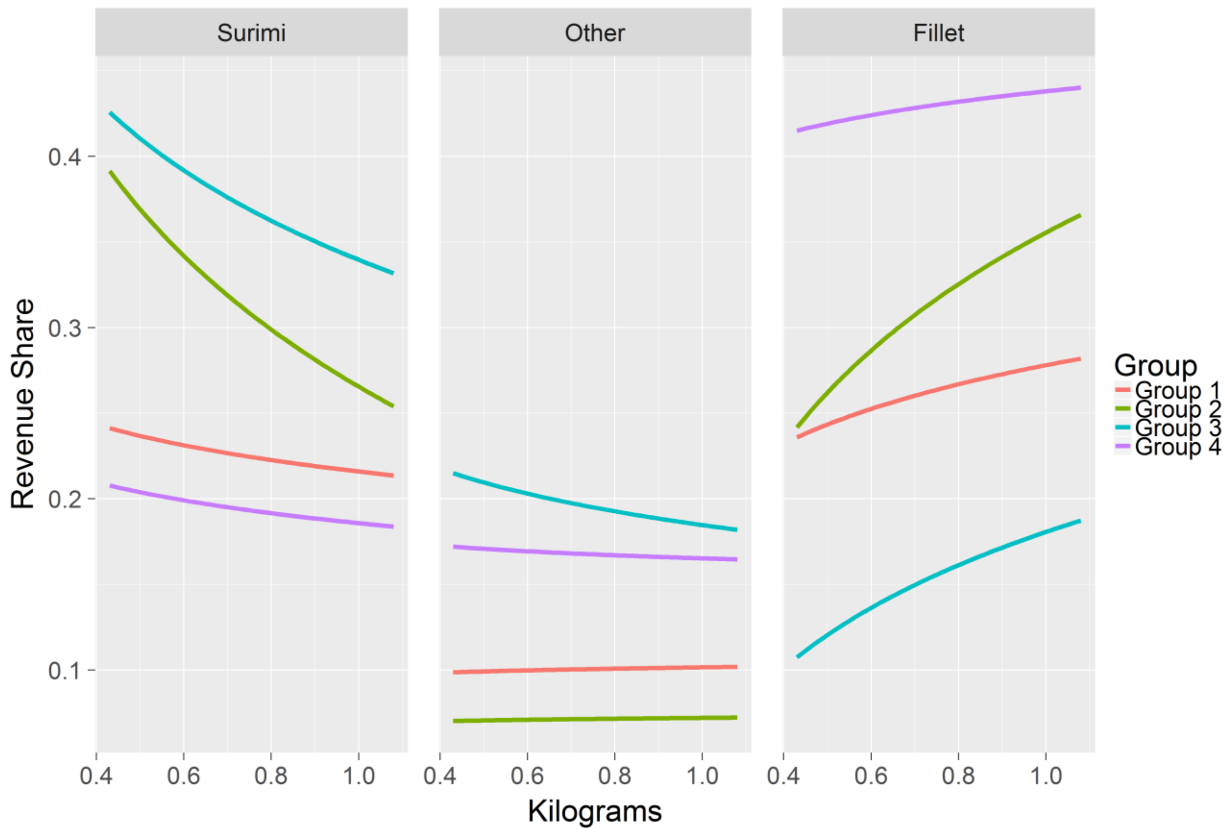

Figure 2.2: Impact to product revenue share by group

Second, we find that substitution across product types alone is not enough to ascertain whether harvesters have fish size preferences. To see this, we first identify which groups substitute across product types by plotting the groups by surimi and fillet percentages in Figure 2.4, where each data point is a vessel-week. Scatter points represent individual hauls over the entire fleet, while groupings themselves are estimated as two-dimensional normal kernel densities. We loosely characterize each group as follows:

- Group 1: Fillet Non-responders produce primarily fillet, and does not respond to size;

- Group 2: Balanced Responders will opportunistically produce surimi or fillet as size changes;
- Group 3: Surimi Responders produce primarily surimi, but will opportunistically produce fillet as size increases;
- Group 4: Fillet Responders produce primarily fillet, but will opportunistically produce surimi as fish size decreases.

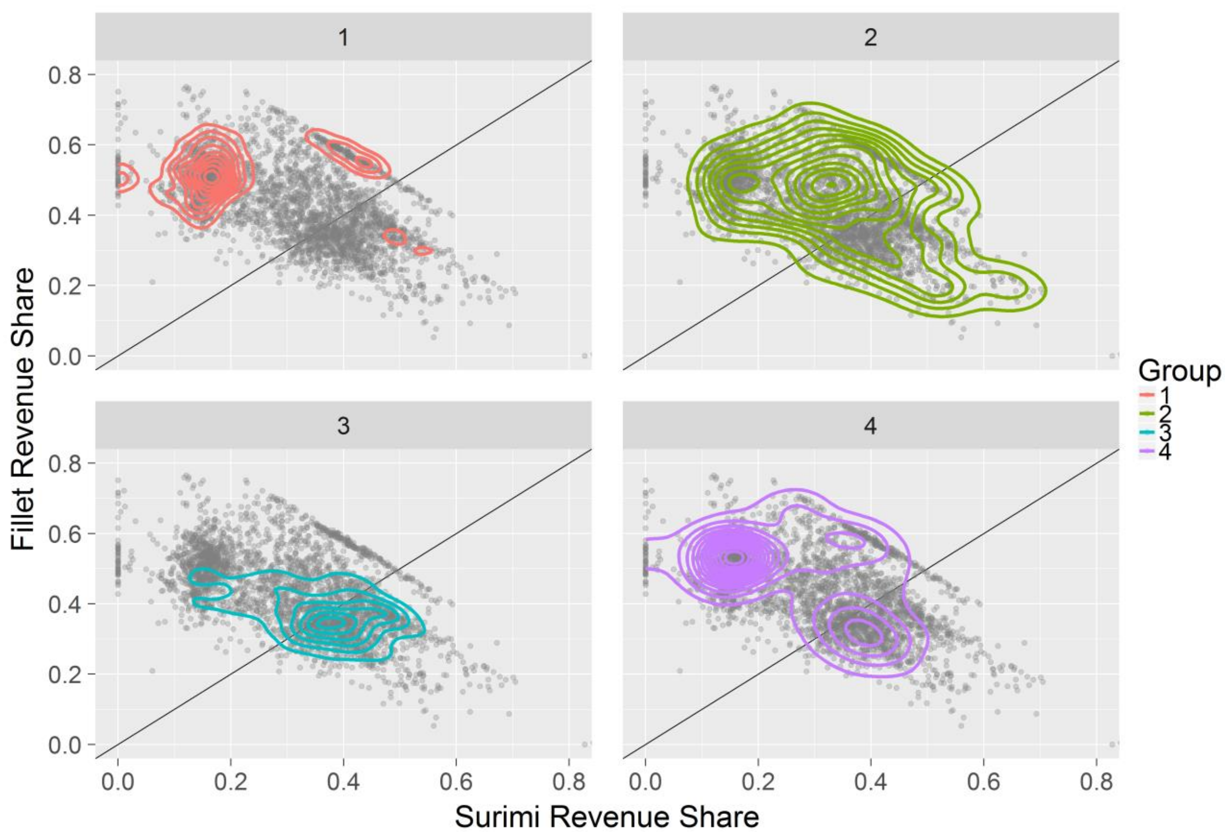

Figure 2.3: Proportion of fillet vs. surimi revenue share by group

By identifying the latent heterogeneity in product substitution resulting from fish size, we can accurately estimate how revenue per unit of quota (unprocessed fish) change with size across vessels. Note that by examining the revenue harvesters receive for their unprocessed fish, we capture underlying differences in recovery rates across products. We calculate the price elasticity of fish size by evaluating the revenue function at its mean values, using the delta method to calculate standard errors.[35]

Fillet Non-responders (Group 1) are the only group that does not produce less fillet as fish size decreases. Therefore, the effect of fish size on their price per metric ton of unprocessed pollock is small, and not significant at a conventional 0.05 level as they are able to produce and sell fillet even with small fish. Fillet responders (Group 4) have a statistically significant response from fish size when fish are small (i.e. less than approximately 0.6 kilograms), but not at the average quantity of fish caught). While they primarily produce fillet as well, they also produce some surimi as necessary. Because grouping is based on responsiveness to size, two vessels that have different production strategies may be similarly unresponsive to size.

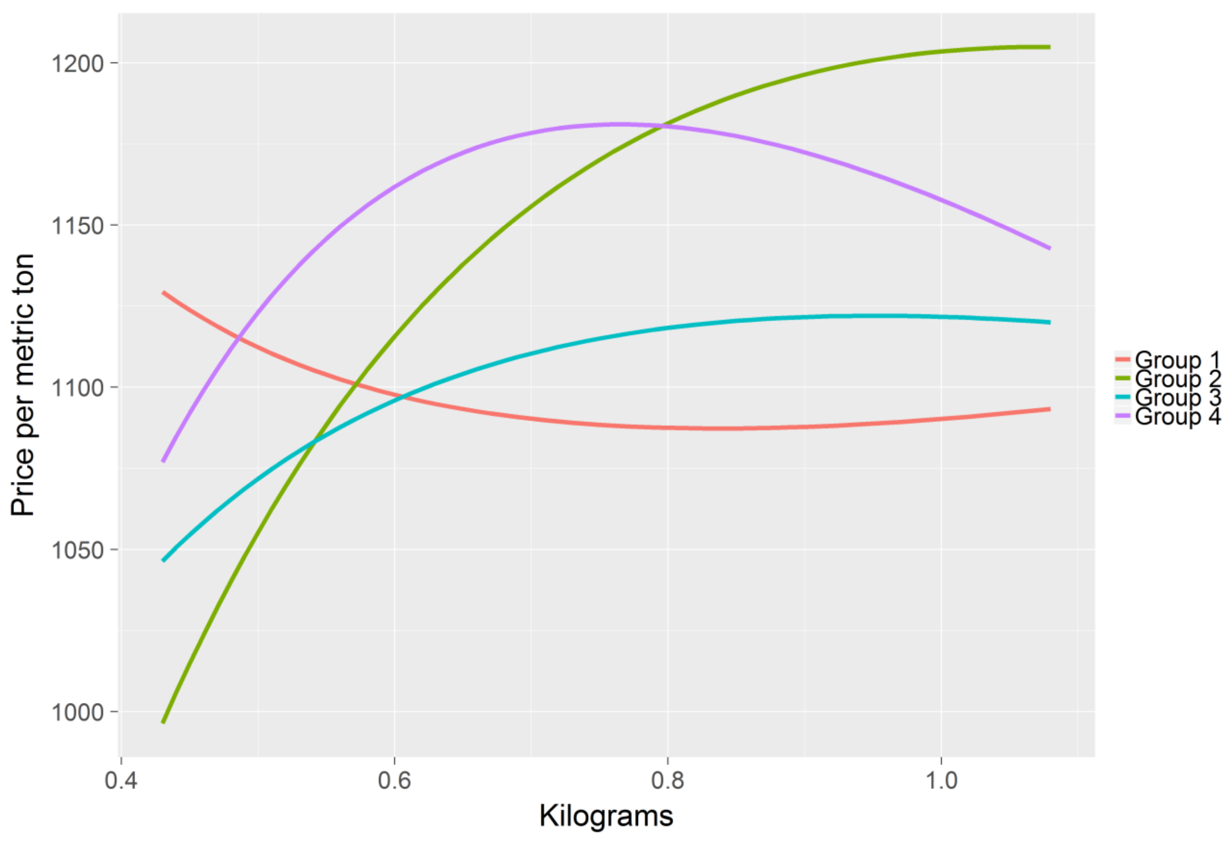

Figure 2.4: Price per metric ton of pollock caught by group

[35] Note the revenue function can be rewritten as log(revenue)-log(weight of unprocessed fish) by subtracting log(weight of unprocessed fish from both sides).

Table 2.4: Price elasticity with respect to fish size

	Group 1		**Group 2**		**Group 3**		**Group 4**	
	Beta	*SE*	*Beta*	*SE*	*Beta*	*SE*	*Beta*	*SE*
WPF	-0.026	0.044	0.211*	0.038	0.081*	0.033	0.077	0.048

2.3 WELFARE SIMULATION: A DYNAMIC AGE-STRUCTURED BIOECONOMIC MODEL

By identifying how production technology, market access, and relative prices result in heterogeneous fish size preferences in the pollock fishery, we can better estimate the welfare impacts from changes in fish size. We simulate how different harvesters target fish size (relative to the average available fish size of the biomass), given the estimated production relationships in the previous section. We find that when vessels are heterogeneous, harvesters whose revenue is not relatively affected by the size of fish they catch tend to catch younger, smaller fish. This imposes a negative externality on other members of the fleet, including harvesters that prefer larger fish. Harvesters come to rely on lower-valued products, and in addition, the value of the fishery is decreased as the overall rate of growth of the biomass declines.

We use a non-cooperative model of a time-differentiated and age-structured fishery with 5 heterogeneous representative agents with an equal share of the total allowable catch, where each agent chooses the size of fish to target. Each agent represents one of the estimated groups, which may contain more than one vessel, but in the interest of parsimony we model each group as a representative agent.

Each agent i has its own price curve, equal to the 4 heterogeneous price curves estimated previously, where the price for fish aged a is given by $p_{i,a}$, with a maximum age A, and discount factor δ. For the vessels whose price elasticities are not significantly affected by fish size, we take the mean of their prices across all sizes. In each time period t, each agent chooses the smallest age to target, $\underline{a}$, harvesting $s_{i,a,t}$ kilograms of fish at each age above $\underline{a}$, incurring a cost $c(f_{i,t})$ as a function of fishing effort $f_{i,t}$. The net present value from participating in the fishery for each agent is therefore equal to

Equation 2.5: Net present value for fisher

$$\pi_i = \sum_{t=1}^{\infty} \sum_{a=1}^{A} \left(p_{i,a} * s_{i,a,t} - c(f_{i,t}) \right) \delta^t.$$

To calibrate our fishing effort we run a regression to find the impact fish size has on the total number of haul hours, defined as the sum of all haul durations in that year, for a given harvester. Then, by using historical data on the relationship between time spent fishing and total trip duration, we derive yearly operating costs. For the 17 catcher-processors in our sample, we calculate the difference between the mean weight of fish the harvester caught in year *t*, and the average weight of available fish in year *t*, or $Weight\ difference_{it}$.

The average weight of available fish is the average of the mean weight-at-ages for ages 3-7, weighted by the numbers of fish in each age class, from the Bering Sea pollock stock assessment (Ianelli et al. 2016).[36] This measures the effect of catching larger fish compared to the size of available fish on fishing duration.

We also include the total weight the harvester caught in that year, the variance of weight in haul (averaged over the year for a harvester), and the interaction between the average weight per fish difference and total weight caught as regressors. When harvesters catch more fish, we hypothesize they would spend more time fishing, and we also hypothesize that the effect from catching larger fish may depend on the total quantity of catch the harvester must fulfill in that year. We include group and year fixed effects to control for differences across vessels and changes in biomass across years.[37]

[36] Tables 1.25 and 1.30 in Ianelli et al. 2016. We assume there are five fishable age classes, and ages 3-7 comprise slightly more than 80% of historical catch on average in a year. The effect of the truncation at year 7 is to bundle all year classes greater than 7 in a "plus group", implying their growth in value and weight is negligible after year 7.
[37] The adjusted R^2 without year fixed effects is 0.654.

Equation 2.6: Fisher cost function

$$Hours\ spent\ fishing_{it} \sim \beta_0$$
$$+ \beta_1 * (Weight\ difference_{it})$$
$$+ \beta_2 * (Total\ weight\ caught_{it})$$
$$+ \ \beta_3 * (Weight\ difference_{it} * Total\ weight\ caught_{it}) + \varepsilon_{it}$$

Table 2.5: Fishing duration as a function of fish size

Hours spent fishing

	Beta	*SE*
β_0	404.768*	124.418
β_1: *Weight difference*	-154.114 *	37.306
β_2: *Total weight*	0.023*	0.003
β_3: *(Weight difference*Total weight)*	0.007*	0.001
Group fixed effects	Yes	
Year fixed effects	Yes	
R^2	0.853	

In Table 2.5 we find that an increase in the total weight caught in a year increases the time a harvester must spend fishing. The effect of an increase in fish size on the time a harvester spends fishing is given as $\beta_1 + \beta_3 * (Total\ weight\ caught_{it})$, which is positive for yearly catches greater than approximately 22 thousand metric tons. Evaluated at the average total weight caught in a year, 36 thousand metric tons, the effect of a 0.1 kilogram increase in the mean weight per fish is associated with 98.76 additional hours spent fishing on average (standard error 31.19).

An increase in the size of fish a harvester catches will cost a harvester more time, the greater of quantity of fish they catch that year. One reason may be that the greater quantity of fish a harvester must catch, the more difficult it becomes to find larger fish which are decreasing in abundance as catch increases. Therefore although the agent is allowed to be selective, more effort must be expended if the agent chooses to be more selective, and search for a small subset of ages.

To calibrate the cost of one day of operation, we convert haul hours to operation hours by noting that on average the total time a vessel is operating is 2.16 times the number of hours actually spent fishing.[38] We then estimate our model, evaluated at the average group and year fixed effects, for a range of operating costs per day traveled (40 thousand to 90 thousand dollars per day).[39]

We model the stock dynamics at a yearly level (accounting for growth and mortality of an age class as they age one additional year), where $N_{a,t}$ represents the number of fish aged a that exist in year t. Therefore the decision to target certain age classes by choosing a minimum age should be thought of as the average size the harvester targeted in that year. For each age, we parameterize one weight ω_a, the average weight of that age class, using average weights at age from the pollock stock assessment (Ianelli et al. 2016). Each harvester maximizes their profit by selecting the smallest age to target, subject to a series of equations describing the population dynamics of the fishery which keep track of the number of fish at each age over time as a function of harvest. The full maximization problem of harvester i, including the population dynamics and quota constraints, as well as additional information on the approximation method, can be found in the Appendix.

This maximization problem for each representative harvester, conditional on the actions of other agents, can be stated with a Bellman equation,

Equation 2.7: Fisher value function

$$Value_i(\widehat{N}) = \max_{0<s_{i,a}<N_a*\omega_a} \left(\sum_{a=1}^{A}\left(p_{i,a} * s_{i,a,t} - c\left(f_{i,t}\right)\right) + \delta EV(\hat{\hat{g}}\,(s_{i,a}, s_{-i,a}, N_a))\right).$$

To solve for the non-cooperative best responses we approximate this value function by use of a collocation method (Judd 1998). The solution to the noncooperative problem takes the form of

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[38] Data designating trip start and end dates begin in year 2008. We calculate this ratio using trip data beginning in 2008, to convert fishing hours to operating hours, while using the full data set (2003-2013) to estimate the effect of fish size on fishing hours.

[39] These estimates of operating cost per day are based on correspondence with harvesters, and other estimates of catcher-processor operating costs of similarly sized vessels operating on the West Coast (Table 10.1 Harley et al. 2015). Harley et al. report average variable costs per day of 57-83 thousand dollars in their data set spanning 2009-2012, which are comprised of primarily crew compensation and fuel,

three (m^5)-by-V matrices of best responses, basis coefficients, and value function approximations at the collocation nodes. The order of the Chebyshev polynomial[40] is denoted m, and the number of representative agents V=4.

2.3.1 *Non-cooperative behavior results*

Harvesters primarily compare the increase in expected price from larger fish versus the cost of searching for those fish, and we show that any potential increase in value from additional harvest and future biomass is discounted to the extent the harvester must share that value with its competitors. Therefore, harvesters whose revenue are not relatively affected by fish size will target a broader selection of age classes, as they are relatively indifferent towards fish size. We show that the benefits from incentivizing the selection of large fish in the pollock fishery result not only from the production of more valuable products, but that the majority of forgone value is actually due to additional harvest and future biomass, which cannot be internalized by the individual harvester under current institutions.

We use the solutions from the maximization problem which give best responses of each harvester at the collocation nodes, to simulate the behavior of harvesters over 20 years, interpolating across state nodes. The fishery is initialized at the size structure given in the assessment in the year 2003 (the starting year of our data), and pulls recruitment in each year from the lognormal distribution specified above. Results are then averaged across the cost parameter space and the last 10 years of the simulation (to allow for burn-in).

Figure 2.5 illustrates that noncooperative harvesters tend to target smaller ages than a fishery manager would choose. Recall that the choice variable for the harvester is to choose the youngest age class to target in a time period, and harvesters catch fish from that age class and all classes above it (i.e., knife-edge selectivity). Fillet Non-responders (Group 1) and Fillet Responders (Group 4), harvesters that do not have strong fish size preferences, target the minimum fishable

[40] We tested our models using different orders of Chebyshev polynomials, and the results are presented for 8th order polynomials. We found lower-order polynomials could provide poor approximations (e.g. not converging on optimal solutions when the order was below 5), and our results remained robust after increasing the order past 8, while increasing computational time.

age-3 class on average. Heterogeneity in how revenue is impacted by fish size implies that some vessels naturally find it worthwhile to incur larger costs to search for larger fish, while others do not. However, the harvesters who target smaller fish negatively affect the value of the fishery to a greater extent (note that Groups 1 and 4 tend to be further from the socially optimal actions), and this results from a failure to internalize increases in future harvest from faster biomass growth.

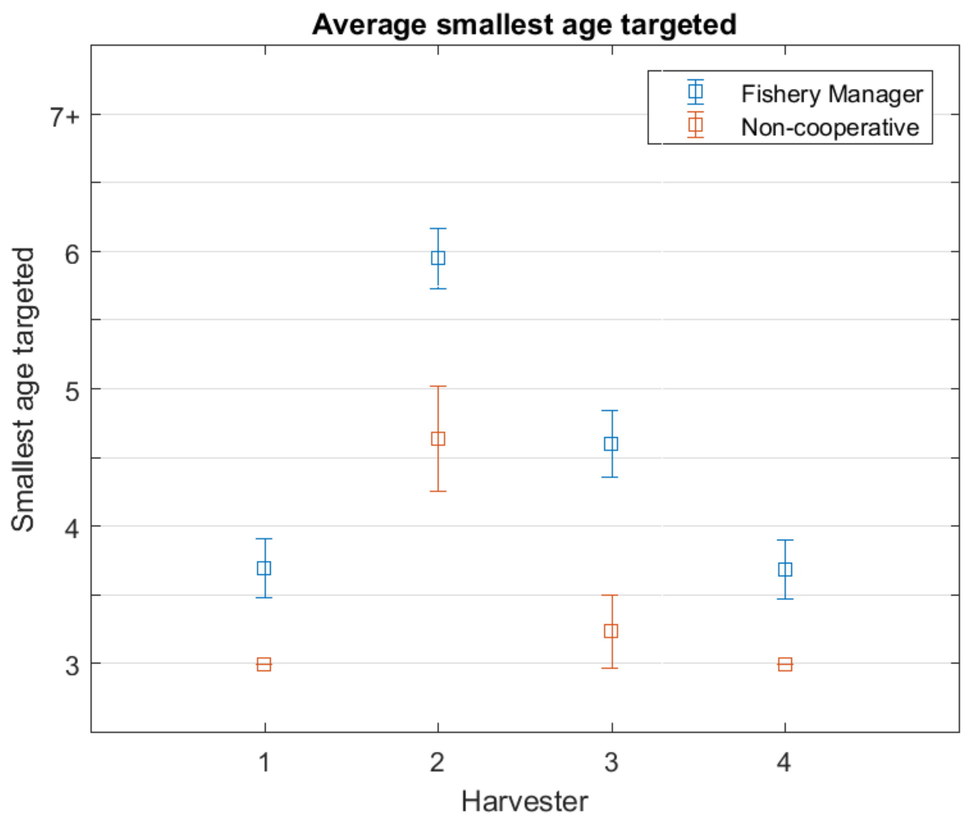

Figure 2.5: Smallest age targeted

To understand why harvesters would be willing to target smaller fish, we examine the extra days spent fishing when harvesters search for larger fish, and Figure 2.6 shows that when operating costs per day are relatively low, a harvester who could increase their revenue substantially will choose to send more days fishing (e.g. a Surimi Responder in Group 3).[41] Conversely, Group 1 and 4 harvesters, who generally make fillet regardless of fish size or receive high surimi prices

[41] Note that this is the number of operating days the fleet (i.e. multiple vessels) takes to catch their quota of fish, and the manager has bequeathed identical quotas to each fleet.

respectively, fill their quota in a shorter number of days by targeting a broad range of age classes. However, as operating costs increase, it becomes unprofitable to search, even for the Group 3 (Surimi Responders) processors. Harvesters will choose to increase their selectivity only as much as increases in operating costs allow them to.

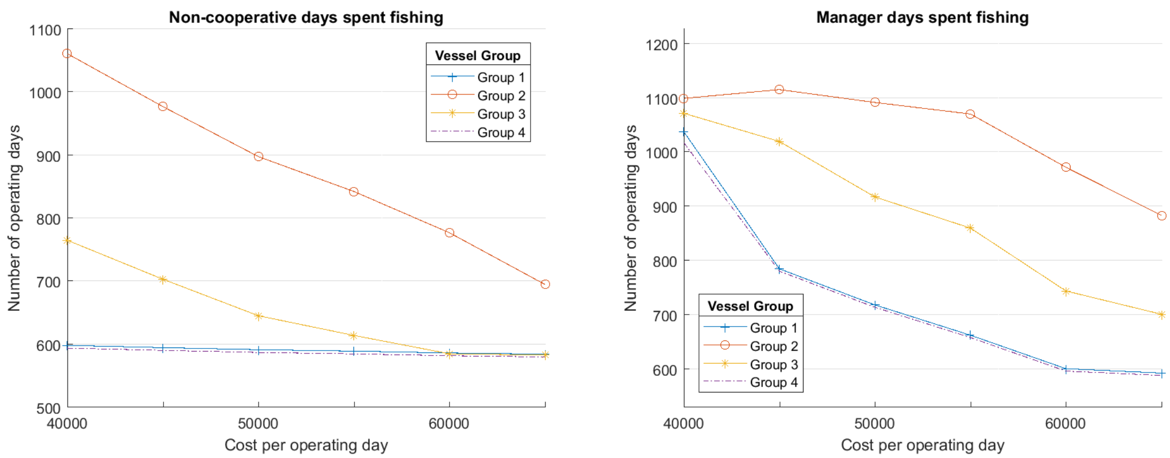

Figure 2.6: Days spent fishing (manager versus noncooperative)

To maximize the value of the fishery harvesters would spend more time fishing, catching larger fish, although as operating costs increase it is still optimal to be less selective and operate fewer days. This is because while there is potential value in encouraging production strategies that encourage selection of larger fish, creating more valuable products, selection of larger fish may not always be in the individual fisherman's interest. Individual fishermen make tradeoffs depending on their own preferences for fish size and operating costs.

However, the potential for increases in total fishery value also include forgone value from larger harvests due to a more productive, faster-growing stock, in addition to increases in value due to changes in product mix. A fishery manager takes the forgone value from future harvest into account, net of cost increases. As a result, they find that when harvesters without strong fish size preferences spend more time searching for large fish, total fishery value can increase.

Figure 2.7 shows that when harvesters in Group 1 or 4 choose to spend fewer days fishing and catch smaller fish, this affects the overall biomass rate of growth because smaller fish grow faster; the value from leaving them in the fishery is greater than fishing them in the current time period. While there are slightly more age 7+ fish under non-cooperative exploitation, because there are more harvesters willing to catch smaller fish and the largest age class is not fished as heavily, the biomass in aggregate across all age classes is larger under a fishery manager. A greater quantity of younger fish are left to grow, and when total biomass is greater, each individual harvester's quota increases as well, since quota is determined as a fixed percentage of biomass.

In addition, when larger fish are targeted, they are transformed into more valuable products. Non-cooperative harvesters catch fish approximately 0.1 kilograms smaller on average (Figure 2.7), and we note again that the largest differences occur with noncooperative harvesters whose revenues are not as affected by fish size. All noncooperative harvesters make less valuable products on average because they catch smaller fish.

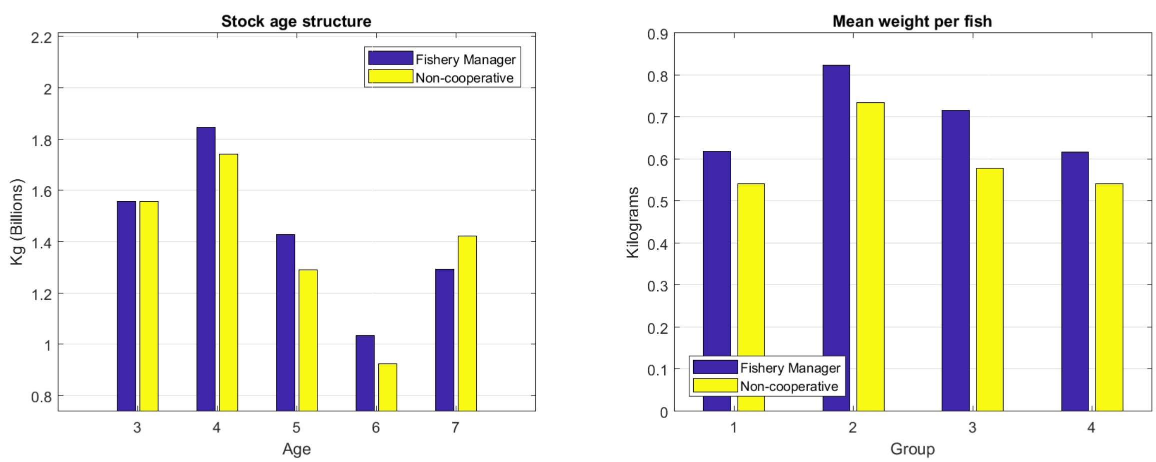

Figure 2.7: Stock structure and mean weight per fish caught

We can decompose the increases in revenue to find out how much is due to increases in prices, versus increases in quantity (increased harvest). Figure 2.8 shows that the majority of the feasible increase in revenue is due to the change in quantity of fish caught, due to reduced biomass and therefore reduced catch under non-cooperative behavior. Fleet-wide increases in prices account for approximately 20 percent of the increase in revenue. In addition, gross revenue increases on average by approximately 5 percent. Approximately 75-80 percent of this revenue increase is due to increases in harvest, however. This suggests there are large benefits to incentivizing selection of larger fish beyond product transformation. However, the benefits from increases in future harvest are not internalized by non-cooperative harvesters because only a fraction of future value of young fish will be recovered by individuals.

We also note that increases in costs from being more selective are less than increases in revenue[42]. A fishery manager that internalizes the future value of smaller fish due to larger biomass would choose to be more selective, because for each harvester the increase in operating cost is smaller than the increase in revenue they would receive, *when we take increases in future harvest into account*.

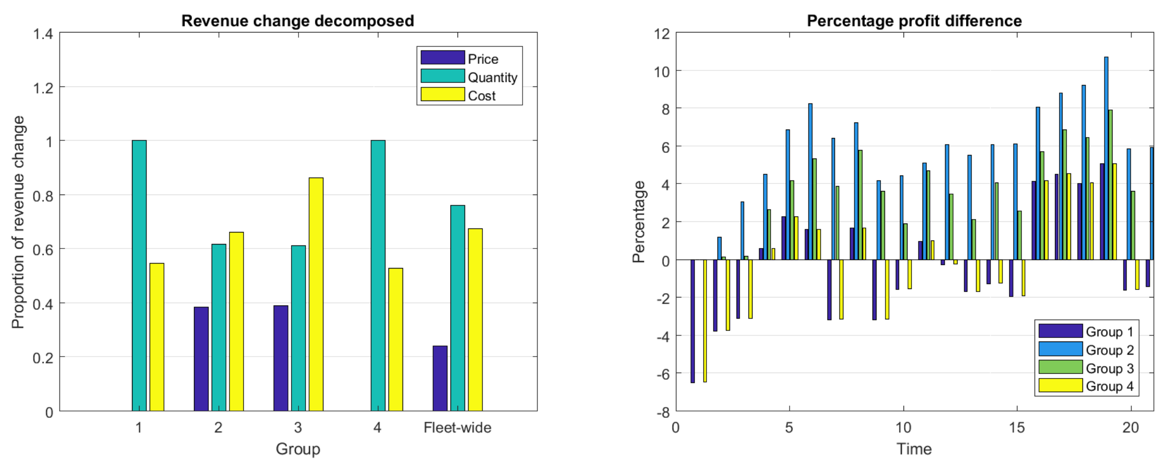

Figure 2.8: Percentage changes in profit and revenue decomposed

Therefore, while gross revenues increase by an average of 5 percent, and a proportion of the benefit from incentivizing selection from larger fish is due to production of more valuable products, the increase in harvest comprises the largest share of increased revenue.[43] A large part of the increase in potential fishery revenue is due to the biological dynamics of leaving younger pollock in the ocean to grow.

[42] Recall that being more selective is to select a smaller subset of ages, as the fishery manager would suggest.

[43] An 5-percent annual increase in revenue in the pollock catcher-processor fishery would correspond to more than 30 million dollars per year.

The gains are not equally shared among all harvesters, however. Effective management with respect to size may require certain harvesters to take a monetary loss now in order to increase profits in the future. Figure 2.8 also illustrates the change in profit (revenue net costs) when operating costs are assumed to be $40,000 a day. Surimi responders (Group 3) can increase their profits by more than 10 percent in a year under size-selective management. However, the costs of the Fillet Non-responders and Responders (Groups 1 and 4) exceed their revenues in many early years, although all harvesters benefit in future years from larger biomasses and larger harvests.

2.3.2 *Retrospective analysis*

As a retrospective analysis we show the potential gains in biomass and harvest for low-pollock years in 2009 and 2010, had the fishery been managed for size. First we initialize the model with the numbers-at-age from the pollock assessment for the year 2003 (Ianelli et al. 2015). From the assessment model we also take as exogenous the age 3 recruitment, the percentage of the biomass allocated as allowable fishery catch, and time-varying weights-at-age, for the years 2003-2013.

As the policy functions for each representative harvester (estimated from the previous section) dictate selectivity as a function of the state of the stock, we can simulate numbers-at-age for subsequent years endogenously. Then, we compare the dynamics of the fishery in our simulation had we managed for size (“simulated fishery”), to what actually occurred in the observed fishery as estimated by the stock assessment model (“true fishery”). Even though recruitment, weight-at-age, and allowable catch as a percentage of biomass for each year are identical between the simulated and true fishery, we show large gains in catch and biomass, particularly in the low-pollock years Figure 2.1Figure 2.9).

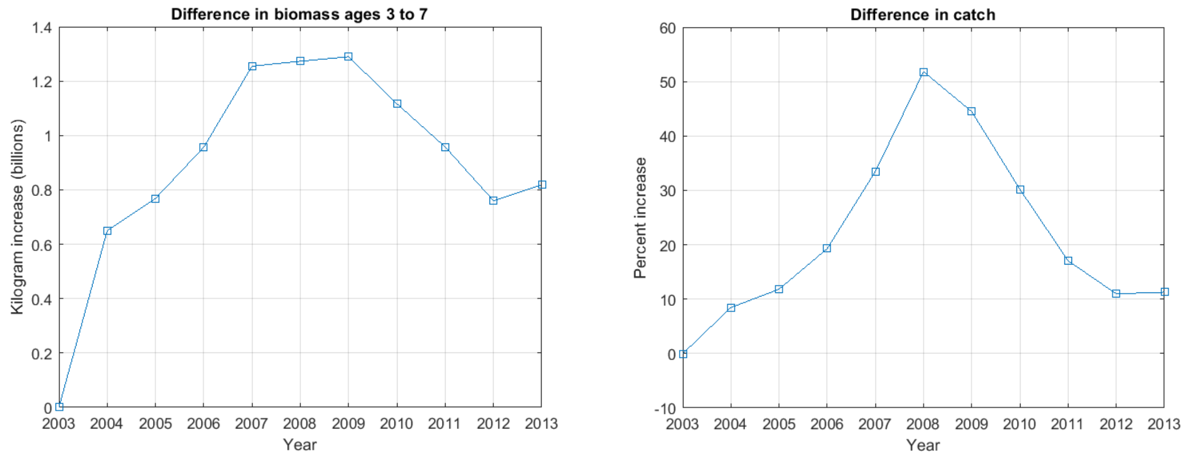

Figure 2.9: Difference between simulated and true fisheries

Percentage increases in catch peak at above 50 percent in 2008, while biomass peaks at an additional 1.3 billion kilograms in 2009 (the average biomass for the years 2003-2013 is 5.37 billion kilograms, ages 3 to 7). Recall that we have taken the historical percentage of biomass allocated as catch in each year as given. Therefore, as biomass increases due to faster growth from leaving younger fish in the fishery, catches must increase as well.

There are a number of caveats, namely that allowable catches decreased in the true fishery for the years 2009 and 2010, largely due to declining biomasses in 2007 and 2008. Even though this decline is less sharp in our simulated fishery due to more efficient management, we keep the percentage of biomass allocated as catch the same. One can imagine with a healthier fishery, a larger quantity of catch might have been allowed. In addition, we take weights-at-age and recruitments as exogenous from the assessment model. This assumes they are independent from the development of the stock and the distribution of numbers-at-age over time.

Still, there is evidence that harvesters would have been able to catch a greater quantity of fish, and the health of the fishery would have improved, had the fishery been managed for size. Interestingly, the largest gains occur when the fishery suffers its greatest declines. Because these years are characterized by smaller-than-average recruitments, it is unlikely size-based management alone would completely reverse the decline in low-pollock years. However, in the simulated fishery harvesters enjoyed large increases in allowable catches, and the greatest benefits occurred when catches were curtailed the most due to declining stocks.

2.4 DISCUSSION

In this chapter we estimate the sensitivity of harvest revenue to the average size of pollock caught in the Bering Sea pollock catcher processor fishery. We show that larger fish can be made into more valuable products, and harvesters vary in how responsive they are to changes in the size of fish they catch. This has several implications. First, this provides additional evidence that size-based management can increase the value of the fishery, because size-responsive harvesters can substitute to more valuable fishery products with larger fish. When harvesters catch larger fish they increase their fillet revenue share and do so by substituting away from lower-valued surimi.

When harvesters are heterogeneous, however, other harvesters have no significant change in revenue due to changes in fish size. In this scenario, a harvester with a production strategy whose revenue is not sensitive to changes in fish size tends to catch smaller fish that grow at a fast rate. Management that eliminated this race would result in greater harvests for all fishermen, in addition to the production of more valuable products. Non-cooperative harvesters do not internalize the future value of young fish (net the cost of being more selective).

By identifying the latent group structure in the catcher-processor fleet, we find that vessels who share similar sensitivity of revenue to size of pollock do not necessarily share similar production strategies, as market access and the relative prices of substitute products also play a role. Therefore, a harvester that always produces lower-valued fillet, and a harvester that substitutes from fillet to relatively high-valued surimi when the size of fish caught decreases, can both be indifferent towards the pursuit of large fish.

Understanding how harvesters are responsive to size allows fishery managers to predict the severity of the race to catch younger fast-growing fish, because if harvesters prefer larger fish sizes they will participate in the race less. It is possible, but certainly not necessary, that the price premium for larger fish would encourage efficient targeting.

However, when there are multiple production strategies that are indifferent to the size of fish, certain fishing strategies detrimentally impact the value of the fishery more than others. Looking at product choice alone will lead to incorrect inference about how much a harvester responds to size, and which production strategies add the most value to the fishery. Due to the race to catch younger fish in the pollock fishery, individual harvesters have weak incentives to choose a production strategy that makes more valuable products made from larger fish, as young fish are not spared to grow regardless of the individual harvester's actions. By assuming all vessels share identical preferences for fish size, this externality can be underestimated.

These results are specific to the pollock fishery to the extent that the stock-recruitment relationship here is weak. Because the fishery is characterized by extremely large recruitment classes that do not have a strong correlation with the standing spawning biomass, we modeled recruitment as a stochastic process. As a result, the primary biological difference between larger and smaller fish was the rate of growth.

Research in other fisheries suggests that larger fish may also affect biological dynamics through avenues such as increased fecundity in larger fish (Birkeland et al. 2005), or the endowment of hereditary characteristics such as growth rates to offspring (Guttormsen et al. 2008). In these fisheries a larger impact to revenue from fish size may instead have a detrimental effect.

In addition, as the volume of high-value products increases, we should expect potential impacts on prices. Prices in this fishery are pre-negotiated before the season begins, and they do not vary within a year, for a specific product. However, if more vessels produce high-value products this may affect prices over the long run.

Lastly, in the U.S. Bering Sea and Aleutian Islands the total allowable catch of groundfish is capped at 2 million tons. Because the majority of the increase in revenue is due to a larger biomass and increased quotas, some of the stock benefits for the pollock fishery may be constrained by this cap in some years. Even if the increase in pollock biomass allowed fishery managers to increase pollock quotas, they may not be able to do so without decreasing other groundfish quotas.

These caveats highlight the intricacies of management with respect to the dimension of fish size. For example, a standard solution to size-structured extraction is often pulse fishing – waiting for fish to grow to an optimal size, while abstaining from harvest until then. Because closing the fishery for extended periods of time may not be a realistic policy alternative, here we examine other types of management with respect to size selectivity. However, due to the heterogeneous preferences of participants in the pollock fishery and costliness of size selectivity, we still find that future increases in profits may require certain harvesters to take a profit loss in the short run.

Accurately quantifying the effect of size selection on a fishery will require examining the composition of vessels participating in the fishery. When only some vessels choose to select smaller, younger fish, financial losses impact all fishery participants in the long run. Even though strategies that respond to changes in size through substitution to higher valued products could increase revenues on average by more than 30 million dollars per year, and profits by up to 10 percent in a year, collective action may be difficult. Although harvesters who take a profit loss in the short run may be better off in the long run due to increased harvests, capital formation and time preferences may dictate an unwillingness to make these tradeoffs.

Due to the relationship between existing processing equipment and size selectivity, a natural extension for future research is to examine how long-run transitions in capital may be driven by changing biological conditions. A number of catcher-processors have undergone refittings in the span of our data set, for example increasing their capacity to produce fish oil and fish meal as demand for those products increases. Because product choice has a direct effect on the sustainability and health of the fishery stock, it is essential to understand to what extent capital formation is strategic with the intent of impacting size structure, or if it is a reaction to long run changes in the fishery.

Chapter 3. RATIONALIZATION BASED ON FISH SIZE IN THE BERING SEA POLLOCK FISHERY

Traditional weight-based quota regulation does not distinguish between different sizes of fish, even though different sizes of fish may have different biological and economic characteristics. For example, larger fish may be more valuable per weight because they can be transformed into different product types. Larger fish may also be older and grow at a slower rate compared to younger fish, or be less abundant due to natural mortality and therefore be more costly to catch.

By using a structured model to investigate changes in a fishery (the seminal example of Leslie (1945)), scientists can account for the fact that when fish are different sizes, they have different growth rates and different economic values. While stock assessment models are typically age-structured (Fournier and Archibald 1982), development of bioeconomic models that do not treat the population as a single biomass are relatively new (Tahvonen 2009), and typically examine the optimal actions of a single fishery manager (Kulmala 2008). Other economic studies of how size selectivity affects fishery yield and value (Thunberg 1998), or how a fishery species may contain a diverse set of traits that change over time (Smith et al. 2008; Sterner 2007), impose an empirically-estimated selectivity pattern or vary selectivity exogenously without examining why harvesters choose the observed actions.

Effective management must consider the biological and economic heterogeneity in fish size because harvesters can include fish size in their decision-making behavior by targeting certain sizes. Selection of specific sizes occurs by spatially targeting schooling sizes, or by changing fishing gear, but when harvesters have the ability to transform larger fish into more valuable per pound products, harvesters must make a tradeoff between selecting large valuable fish and more abundant smaller fish. Analysis of a noncooperative structured bioeconomic model shows that exploitation by multiple agents encourages each harvester to decrease harvesting costs even in the presence of individual quotas, causing them to fish smaller size classes than socially optimal (Diekert 2012). The extent of rent dissipation, however, depends on the biological and economic characteristics of the fishery, including the extent that larger fish are more valuable per unit weight.

When harvesters must increase effort searching for specific sizes and spend more time to catch the same quantity of quota, they may find it costly to select sizes that are less abundant. In this chapter, we show noncooperative harvesters can decrease costs and increase current-period profits by targeting more available, smaller sizes, even when larger fish are more valuable per-weight. This behavior causes two dynamic stock-structure externalities. First, if smaller fish grow at a faster rate, this behavior does not account for a stock-growth externality that slows the biomass rate of growth, decreasing future quotas. Second, because small fish are not left to grow a skewed-size-structure externality leaves fewer large fish in the future, increasing the targeting cost from searching for larger fish for all participants. Weight-based regulations undifferentiated by size, even when a fishery is rationalized throug individual tradable quotas (ITQs), do not weaken the indivdual incentives to target based on size and ignore the externality on the population.

This chapter develops a dynamic age-structured model to investigate how variable economic and biological characteristics across size affect the magnitude of rent dissipation through identification of the stock-growth and skewed-size-structure externalities. This is to our knowledge the first examination of a noncooperative model that is time-differentiated, which allows us to numerically approximate the approach path to an equilibrium, and to suggest a policy tool that allocates quota based on the size of fish caught. This results in harvesters catching a greater quantity of fish over time without decreasing steady-state biomass.

The next section presents the dynamic structured bioeconomic model, followed by a description of the fishery. Then, we illustrate how interactions between economic price, cost, and biological growth and recruitment affect harvester choices and welfare. Finally, we conclude with implications of a size-based policy tool.

3.1 METHODS

In order to take into account different values at different sizes, and the fact that different ages grow more slowly as they age, our age-structured population model must keep track of the number of fish $N_{a,t}$ at given age a and time t. Age will be described as discrete, while the numbers within each age class will be described as continuous. Fish increase in size as age increases, and we describe the size of each age class as the mean size (in weight) of that age class ω_a, which does not change over time. [44] Each age class therefore corresponds to a single size, the mean weight of that age class. We estimate the model for multiple harvesters, and while some exhibit a significant price incentive to catch larger fish, some may not be responsive to size. The i^{th} harvester catches a weight in kilograms $s_{i,a,t}$ from a given age at a given time. [45] The harvesters can be differentiated with different price functions per size.

We use data from the Alaska walleye pollock stock assessment as a baseline to calibrate the growth rate and average weight at each age. This assumption implies that life history traits (such as growth rate or birth rate) are stable over time. We do not investigate evolutionary changes to life history traits, but how competition pressures harvesters to choose socially inefficient sizes compared to a benevolent fishery manager who maximizes the net present value of the fishery as a whole, taking the profit functions of individual harvesters as given. While it may be socially optimal to keep certain sized fish in the fishery, the common pool nature of potentially future gains provide very limited incentives for harvesters to do.

For the traditional quota representing current regulations, each harvester takes the catch-by-year in the fishery as a whole (regulated total allowable catch in kilograms, *TAC*) as given, where the TAC is a proportion of the biomass for the year. This is similar to how acceptable biological catches are recommended in the stock assessment, as a proportion of the estimated stock size, by weight. Each individual harvester is able to harvest *TAC/V* where *V* equals the number of harvesters in the fishery. The harvesters therefore share an equal proportion of the fishery-wide *TAC*, although this is generalizable for different proportions. Because the TAC changes with the biomass, management responds by adjusting the *TAC* as the stock changes,[46] while harvesters

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[44] This implies that the growth rate between two given ages is always the same over time (although not necessarily between ages).

[45] This simplification where the harvester chooses weight, and not numbers, essentially assumes that fish are infinitely divisible, and vessels can harvest some fraction of a fish equal to the kilograms desired. In reality, harvesters must choose numbers, but this allows us to describe the harvester's choice variable in terms of weight, kilograms.

[46] Hritonenko et al. (2012) show that if the rate of growth in value is larger for smaller ages, it can be optimal to always keep fish of a certain age in the fishery. In that case, if the *TAC* exceeds the quantity of fish above that age, it would be suboptimal to bind the harvest constraint.

decide which sizes to target conditional on their share of *TAC*. Because we are interested in how inefficient behavior may occur even when catch is guaranteed to harvesters by a quota in pounds, we make the assumption in our model that catch cannot be reallocated between different types of harvesters, even if certain harvesters may derive more value from a pound of quota. For example, in some fisheries quota cannot be traded between recreational and commercial harvesters, or in the pollock fishery, between the catcher-processor and catcher-vessel fleets, even though catcher-processors transform raw inputs into more valuable products. Other factors such distribution of rents and local community development are important goals in fishery management decisions. Therefore even when catch is guaranteed to individual harvesters in pounds (such as with individual quotas), and regulation is not differentiated by size, noncooperative size selection will still result in inefficient behavior both along the transition path and at the steady state, and the magnitude of this externality depends on the type of fishery.

For the proposed policy tool, we allow the fishery manager to allocate quota in every time period based on the size of fish the harvester targets, by multiplying the quota the harvester receives by a "stock impact factor" (*SIF*), such that the harvester receives quota equal to SIF_{it}* *TAC/V*. The fishery manager chooses SIF_{it} depending on the forgone or additional biomass that would occur from a different selectivity decision. For example, if choosing to target smaller fish decreases future biomass (due to the harvest of younger, faster-growing fish), the harvester must compensate with smaller present catches in their quota, and the SIF_{it} will be less than one. Conversely, a harvester may be able to catch a larger quota in the present period and the SIF_{it} may be greater than one if they are selective and only choose large fish. This is because the impact to the future stock would be smaller and future biomass would be larger, compared to a decision to harvest smaller fish. Notably, a harvester may not choose to harvest a greater quantity in the present, depending on how costly it is for them to be selective.

3.1.1 *Catch technology*

In a given time period, the total weight of catch at a given age, across all harvesters, cannot exceed the quantity in the fishery, or: $\sum_{i=1}^{h} s_{i,a,t} + \sum_{j=1}^{l} s_{j,a,t} \leq N_{a,t} * \omega_a$. The total catch by a single harvester across all ages in a given time period also cannot exceed the quota allocated to that harvester, or: $\sum_{a=1}^{A} s_{i,a,t} \leq \frac{TAC}{V}$, where A is the maximum size in the fishery. Our catch technology is then described as follows. In our model a harvester is allowed to choose both a minimum target age $\underline{a}$ as well as a maximum $\overline{a}$. Then, a constant fishing mortality rate $f_{i,t}$ is applied to each age class targeted. This type of catch technology allows harvesters to avoid larger ages if desired[47], and is consistent with a fishery where the targeted catch schools by size; where fish of similar sizes swim together. Harvesters may avoid large fish by choosing different locations where large fish do not school, or by changing their gear (for example, by using trawl excluders allowing fish of certain shape or size to escape). This technology is similar to the commonly used knife-edge selectivity, which specifies a minimum age-at-catch, but we allow harvesters to avoid certain ages. This describes fisheries where targeted catches school by size and location, but harvesters wish to avoid certain size. The harvester must choose a segment of schooling ages they desire to target, but can choose how selective they want to be, at the cost of increasing their fishing effort.

An important aspect of this harvesting technology is that the less selective harvesters are (by choosing a smaller segment of ages), the more effort they must expend, and the greater their fishing mortality will be for those chosen ages. The fishing mortality, multiplied by the weight at an age, is a function of the harvest of that age by a given harvester, and must obey: $f_{i,t}(\sum_{a=\underline{a}}^{a=\overline{a}} N_{a,t} * \omega_a) \leq \frac{TAC}{V}$. We note this can be interpreted as an age-specific Schaefer catch equation, with catchability equal to unity, where the quantity harvest at an age $s_{i,a,t}$ equals the mortality multiplied by the weight at that age, or $f_{i,t}(N_{a,t} * \omega_a)$. Fishing morality must therefore equal:

Equation 3.1: Fishing mortality

$$f_{i,a,t} = f_{i,t} = \begin{cases} \dfrac{\frac{TAC}{V}}{\sum_{\underline{a}}^{\overline{a}} N_{a,t} * \omega_a} & \underline{a} \leq \text{a} \leq \overline{a} \\ 0 & otherwise \end{cases}$$

[47] As opposed to knife-edge selectivity, where the harvester only chooses a minimum target age, and cannot avoid large fish.

Notably, if the biomass of targeted ages is small relative to the quota being caught, fishing effort must increase. It will be costly to find those particular sizes when they are not abundant, and if the harvester included age classes with more abundant fish, it would be easier to fill their quota. They would not need to search for particular sizes, but could fish on any abundant concentrations of fish they find.

Because the total weight of catch at a given age, across all harvesters, cannot exceed the quantity at that age in the fishery, the fishing mortality for a given age summed across all harvesters cannot exceed unity, or $f_{i,a,t} + \sum f_{-i,a,t} \leq 1$, where $-i$ denotes the choices of all other harvesters. This implies that when harvesters compete for similar-aged fish, the chosen fishing mortality of harvester i will be bounded by the effort other harvesters expend on that same age class; the harvester may not be able to catch as many fish of that size as desired. If the age-specific harvest constraint is not violated, then the fishing mortality is equal to the quantity the harvester is allowed to catch, divided by the total weight the harvester is targeting. The greater the total weight the harvester is targeting, the smaller the fishing morality will be.

The intuitive basis for increasing fishing effort as selectivity decreases is as follows. First, as noted by Diekert (2010), and Beverton and Holt (1957), here fishing mortality and targeted sizes are substitutes. If the harvester chooses a large segment of sizes to target, the total weight (across all targeted ages) the harvester is targeting is large, and therefore the fishing mortality across all ages is small. If the harvester is discerning and chooses a small segment of sizes to target, they must exert a larger fishing mortality to catch the same quantity of quota. Because the targeted sizes are less abundant, harvesters must expend fuel, time, and effort searching for their chosen sizes, and costs will be larger for a given harvest of quota. Fishing mortality here can be thought of as fishing intensity, or effort, and we will use these terms interchangeably. To fish a small subset of ages, a harvester must use greater effort than if he is not discerning about the ages to target.

Second, we describe the harvester's cost function as solely a function of the fishing effort, or $c(f_{i,t})$, such that costs increase with the intensity a harvester must expend, $\frac{\partial c}{\partial f_{i,t}} > 0$. Each harvester's cost function is identical, although their selectivity and fishing effort may not be. When the subset of ages targeted is smaller, fishing effort will be larger and costs increase with fishing effort. Therefore, if a harvester chooses a small subset of ages to target, the harvester must expend more effort searching for those specific sizes to fish out their quota. As the remaining quantity of fish at an age becomes fewer, it becomes more costly to selectively harvest that age. A harvester that is not selective in size can capture the same weight or quota with less effort, because they do not need to expend fuel and time searching spatially for the schools of sizes they desire, and can often fish on larger abundances of fish.

3.1.2 *Stock dynamics*

Let μ_t represents the non-fishing survival rate for each year *t* (unity less non-fishing mortality), with ω_a the mean size (in kilograms) per fish of that age class, and $s_{i,a,t}$ the fishing mortality in kilograms for each age *a*, for the i^{th} harvester. The number of fish in age class *a+1* in the next year therefore equals $N_{a+1,t+1} = \left(N_{a,t} - \frac{1}{\omega_a}\sum_{i=1}^{h} s_{i,a,t} - \frac{1}{\omega_a}\sum_{i=1}^{l} s_{i,a,t}\right)\mu_t$, or the number of fish left at each age after harvest, multiplied by the survival rate, which is not age-specific. Recall for our purposes all fish in a single age class are the same size,[48] and therefore the fishing mortality in kilograms divided by that mean size in kilograms gives us the numbers harvested.

Because there are *(a = 1…A)* total discrete age classes, we allow the numbers of fish in the largest age class *A* to correspond to all fish greater and including age *A*. Because the A^{th} age class corresponds to the numbers of fish aged *A-1* in the last period, as well as all fish in *A* that survived, $N_{A,t+1} = \left(N_{A-1,t} - \frac{1}{\omega_{A-1}}\sum_{i=1}^{h} s_{i,A-1,t} - \frac{1}{\omega_{A-1}}\sum_{i=1}^{l} s_{i,A-1,t}\right)\mu_t + \left(N_{A,t} - \frac{1}{\omega_A}\sum_{i=1}^{h} s_{i,A,t} - \frac{1}{\omega_A}\sum_{i=1}^{l} s_{i,A,t}\right)\mu_t$. The implication of placing all fish aged A and greater into a single age class is that if fish are increasing in value as they age because they are larger, after a certain age and size the price per kilogram no longer increases. This is also to say, all fish in class

[48] We calibrate the size of each age class to be the mean size of that age class, where within a single age class fish are the same size.

A and greater have the same value per kilogram, and therefore can be accounted in a single class for our purposes.

Instead of assuming a stock-recruitment relationship, we calibrate recruitment to be centered on the stock assessment mean,[49] such that $N_{1,t} = \Omega_t$. This system of equations then accounts for the numbers at each age, at each time. The harvester then faces $\binom{A}{2} + A$ discrete permutations of minimum and maximum targeted ages, as well as A continuous states $N_{a,t}$ at each time *t*.

3.1.3 *Production technology*

The model allows the value of a specific aged fish to be different across harvesters. There are many reasons why certain agents may desire particular fish sizes. Commercially, different harvesters may have different underlying incentives regarding choice of fish size. For example, different factory trawlers may have different capital endowments and processing equipment on board, or may have contracted to produce different quantities of certain product forms. If different sized fish are relatively more important in the production of particular product forms, the relative value of those sizes are greater for the vessels producing those products. This also implies different trawlers with different processing equipment or different contracts may target different sized fish.

Similarly, a given species may be targeted by agents who fish both commercially and recreationally. Different agents may place greater value on larger fish versus a consistent allocation; for example, the existence of “trophy” sized fish may be of great value to recreational fishermen, while commercial fishermen would otherwise find a stable and consistent size desirable to mechanically process.

To give consequence to these heterogeneous values, let each age have a different price per unit weight, and allow the price relationship to be different for each harvester, reflecting for example

[49] It is possible to include a stock-recruit relationship as a function of the existing biomass. This would be one way to illustrate the impact from harvesting if different ages or sizes have different fecundity. Harvesting different sizes would then affect the expected recruitment in the next year. In anecdotal conversations with fishery biologists/stock assessment scientists, however, many stock-recruit relationships, such as the pacific hake stock-recruit relationship, are not described well parametrically. A stochastic measure may be more realistic.

different onboard processing technologies. Let the slope of the value functions differ across harvesters, but increasing in age, such that ${\partial p_{i,a}}/{\partial a} > 0$; ${\partial p_{-i,a}}/{\partial a} > 0$. Therefore, the value received as a function of age for a given harvester may increase at a faster rate than another harvester. A model with homogeneous harvesters would only use one price relationship for all harvesters.

3.1.4 *Benevolent fishery manager*

For identical discount rates δ across all harvesters, the i^{th} $(i = 1 \ldots V)$ harvester then faces a net present value equal to $\pi_i = \sum_{t=1}^{\infty}\sum_{a=1}^{A}\left(p_{i,a} * s_{i,a,t} - c\left(f_{i,t}\right) * s_{i,a,t}\right)\delta^t$. Each harvester has an individual choice of harvest at age, and when there is a single harvester (the fishery manager scenario) we allow the fishery manager to make the selectivity decisions of all fishery participants.

The fishery manager's maximization problem therefore obeys the following system:

Equation 3.2: Fishery manager's maximization problem

$$\max_{s_{i,a,t}} \pi = \sum_{t=1}^{\infty} \delta^t \left(\sum_{i=1}^{h}\sum_{a=1}^{A}\left(p_{H,a} * s_{i,a,t} - c\left(f_{i,t}\right) * s_{i,a,t}\right) + \sum_{i=1}^{l}\sum_{a=1}^{A}\left(p_{L,a} * s_{i,a,t} - c\left(f_{i,t}\right) * s_{i,a,t}\right) \right)$$

$$s.t.\ N_{1,t} = \Omega_t$$

$$N_{a+1,t+1} = \left(N_{a,t} - \frac{1}{\omega_a}\sum_{i=1}^{h} s_{i,a,t} - \frac{1}{\omega_a}\sum_{i=1}^{l} s_{i,a,t} \right)\mu_t,$$

$$N_{A,t+1} = \left(N_{A-1,t} - \frac{1}{\omega_{A-1}}\sum_{i=1}^{h} s_{i,A-1,t} - \frac{1}{\omega_{A-1}}\sum_{i=1}^{l} s_{i,A-1,t} \right)\mu_t + \left(N_{A,t} - \frac{1}{\omega_A}\sum_{i=1}^{h} s_{i,A,t} - \frac{1}{\omega_A}\sum_{i=1}^{l} s_{i,A,t} \right)\mu_t,$$

$$\sum_{a=1}^{A} s_{i,a,t} \le \frac{TAC}{V},$$

$$\sum_{i=1}^{h} s_{i,a,t} + \sum_{i=1}^{l} s_{i,a,t} \leq N_{a,t} * \omega_a$$

The fishery manager maximizes the net present value of the fishery taking into account that different vessels derive different values from different sized fish, as well as a cost function that increases as the available weight decreases at selected ages. The implication is that as larger sizes are fished out or were always small, the cost of selectively targeting only those sizes increases. For the fishery manager, this cost function decreases the smallest optimal age at harvest, as it becomes more and more difficult to selectively target a small subset of age classes (due to rising costs). When harvesters are heterogeneous, the fishery manager faces the question of how to apportion catch between harvesters that derive a larger return from larger sizes, and harvesters that are indifferent. This is determined by whether the benefit from facilitating the harvest of large fish by harvesters that value them outweighs increasing the costs of less responsive harvesters, and decreasing the rate of growth of the biomass. The fishery manager may not always apportion the catch of larger sized fish to those harvesters that value it most.

For a given time horizon, we can then find the weight of fish from each age class to be harvested at each year, subject to the catch constraint, that would maximize the net present value of the fishery. If Ω_t is a random variable, the Bellman equation describing the value of the fishery is:

Equation 3.3: Fishery manager's value function

$$V(\hat{N}) = \max_{0<s_{i,a}<N_a*\omega_a} \left(\sum_{i=1}^{h} \sum_{a=1}^{A} \left(p_{H,a} * s_{i,a,t} - c(f_{i,t}) * s_{i,a,t}\right) + \sum_{i=1}^{l} \sum_{a=1}^{A} \left(p_{L,a} * s_{i,a,t} - c(f_{i,t}) * s_{i,a,t}\right) + \delta EV(\hat{g}(s_{i,a}, N_a)) \right)$$

The harvester faces a vector $\hat{N}$ comprising all A states at each time t. The vector of states in the next time period is given by the state transition equations above, such that $\widehat{N_{t+1}} = \hat{g}(s_{i,a}, N_a)$, and is a function of the numbers at each age and the chosen harvests at each age.

3.1.5 *Competitive harvesting*

For *V>1 (i = 1…V)*, each harvester must take into account the actions of other harvesters, or the chosen $s_{-i,a,t}$ of the other harvesters. Because the return per caught weight is monotonically increasing with size, competitive harvesters will always compete for larger sized fish even if the marginal value of larger fish is greater to other harvesters. In addition, decreasing abundance of larger sizes at a faster rate will increase the cost of targeting those sizes, and encourage harvesters to be less selective. Competitive harvesters will suboptimally select sizes across an inefficiently large number of different age classes.

The individual harvester's maximization problem is written as:

Equation 3.4: Noncooperative harvester's maximization problem

$$\max_{s_{i,a,t}} \pi_i = \sum_{t=1}^{\infty}\sum_{a=1}^{A}\left(p_{i,a} * s_{i,a,t} - c\left(f_{i,t}\right) * s_{i,a,t}\right)\delta^t$$

$$s.t.\ N_{1,t} = \Omega_t,$$

$$N_{a+1,t+1} = \left(N_{a,t} - \frac{1}{\omega_a}\sum_{i=1}^{h} s_{i,a,t} - \frac{1}{\omega_a}\sum_{i=1}^{l} s_{i,a,t}\right)\mu_t,$$

$$N_{A,t+1} = \left(N_{A-1,t} - \frac{1}{\omega_{A-1}}\sum_{i=1}^{h} s_{i,A-1,t} - \frac{1}{\omega_{A-1}}\sum_{i=1}^{l} s_{i,A-1,t}\right)\mu_t + \left(N_{A,t} - \frac{1}{\omega_A}\sum_{i=1}^{h} s_{i,A,t} - \frac{1}{\omega_A}\sum_{i=1}^{l} s_{i,A,t}\right)\mu_t,$$

$$\sum_{a=1}^{A} s_{i,a,t} \le \frac{TAC}{V},$$

$$\sum_{i=1}^{h} s_{i,a,t} + \sum_{i=1}^{l} s_{i,a,t} \le N_{a,t} * \omega_a$$

While older ages are worth more, and a harvester can ensure a greater proportion of their catch consists of large fish by selectively targeting older ages, the cost of harvesting also increases as a harvester is more selective. Furthermore, the quantity harvested at an age also depends on the targeted ages of other harvesters. If there are many harvesters targeting the same ages, it will not be possible to fish out individual quotas if the total harvest exceeds the available fish at those ages, and the cost of targeting a small number of age classes increases each harvester's costs. Competition will pressure harvesters to spread out their harvest, and fish smaller ages. In addition, if ages with larger sizes are fished out at a faster rate, the cost of selectively targeting those sizes will increase as well, further encouraging fishing down the age structure. Because the price per caught weight increases with size for both types of harvesters, we also expect the both types of vessels to compete for large fish. In particular, when harvesters are heterogeneous, the even if a harvester is less responsive to changes in size, it still has no incentive to avoid larger fish that the responsive harvesters would derive a larger value from, as by avoiding fish and being more selective, costs of selectivity increase.

We can again express the value of the fishery for the i^{th} harvester as a Bellman, except the state vector $\widehat{N_{t+1}}$ is now given by transition equations that are a function of $s_{i,a,t}$, N_a, as well as $s_{-i,a,t}$:

Equation 3.5: Noncooperative harvester's value function

$$V_i(\widehat{N}) = \max_{0<s_{i,a}<N_a*\omega_a}\left(\sum_{a=1}^{A}(p_{i,a}*s_{i,a,t} - (c(f_{i,t})+B_a)*s_{i,a,t}) + \delta EV(\hat{\hat{g}}\,(s_{i,a}, s_{-i,a}, N_a))\right)$$

Both these models can be described as continuous state, discrete choice models, with *A* states and discrete permutations of minimum and maximum targeted ages. In order to find the optimal control of a multiple-state, multiple-action dynamic programming problem, we solve each using a collocation method, by replacing the Bellman with a system of *n* basis functions with *n* unknowns, such that *n* are the number of collocation nodes. Solving the system such that the Bellman is satisfied at the collocation nodes approximates the value function, and only requires satisfying the Bellman at the collocation nodes rather than all possible states. Solving the nonlinear collocation equation system can be achieved with Newton's method. The method for multiple agents is similar, but with *i* value functions and therefore *i*n* basis functions and unknowns. Agents know both the policies followed by other agents as well as the state of the game, such that the strategies form a Nash Equilibrium in every subgame; our equilibrium concept is a non-cooperative Markov perfect equilibrium. Modified routines found in the CompEcon toolbox by Miranda and Fackler (2004) are used to construct the polynomial basis and solve the collocation system. Approximation of the Bellman equation using Chebyshev polynomials is a method used in fields ranging from structural macroeconometrics (e.g., real business cycle (Kollmann et al. 2011) and neoclassical growth models (Rubio-Ramırez et al. 2006)), to political economy (e.g., dynamic models of legislative bargaining (Duggan et al. 2011)).

The basis functions replacing our Bellman are constructed from a five-variable Chebyshev polynomial basis by forming the tensor products of five m^{th}-order Chebyshev polynomials of the first kind along five state dimensions, where *m* is the order off the polynomial. We perform robustness checks for a number of different order polynomials. In addition, a (m^5)-node collocation grid is constructed by forming the Cartesian product of the five sets of *m* Chebyshev nodes along the five state dimensions. The choice of Chebyshev nodes minimizes the polynomial interpolation error, and the model is solved by using a quasi-Newton method to find the (m^5)-by-1 (for the benevolent manager) or (m^5)-by-V (for *V* noncooperative harvesters) basis function coefficients resulting from the value function approximants at the collocation nodes.

The resulting optimization of the non-cooperative game provides a (m^5)-by-V best response vector for each harvester giving the mutual best responses at each Chebychev node, corresponding to the minimum and maximum ages to target.

3.2 STOCK AND SKEWED-STRUCTURE EXTERNALITIES

We first show how larger sizes are depleted and cost of targeting increases, causing agents to adapt by harvesting smaller and smaller sizes as we transition to the steady state. Higher prices per weight drive harvesters to target larger fish, while higher costs cause harvesters to target smaller fish. Finally, we propose a policy tool to correct the selectivity externality.

The impetuses for our size-value relationship are relatively fast-growing, schooling species such as Alaska pollock or pacific hake. Physiologically the quantity of usable meat as a percentage of the total caught weight increases with size, but moreover, conditional on the available size and existing processing equipment, we empirically observe a greater price per caught weight for larger fish (Chapter 2). This is driven by the ability for processors to convert larger fish to more valuable product forms such as fillet, while smaller fish are more often processed as surimi, which has a lower price per product weight. Therefore, in our model we specifically examine the effect to targeting behavior when larger fish have higher recovery ratios, and produce economically more valuable product forms. Harvesters can be assigned heterogeneous values per unit weight, for a given size, and therefore different types of harvesters will possess different targeting behavior.

At the smallest growth parameter we investigate the weights-at-age correspond to Alaska Pollock ages 3-7, in kilograms. We choose ages 3-7 because they represent slightly more than 80 percent of the total weight of catch in an average year. Our weights at each age class are also increasing at a diminishing rate, such that larger, older fish grow more slowly than young fish. There are two harvesters and each harvester is allocated 15 percent of the total biomass, such that the harvest in each season depends on the pounds of fish available at the beginning of the season. In each year 70 percent of each age class survives due to natural (non-fishing) mortality, with a 5 percent discount for each harvester.

Table 3.1: Functional forms used in numerical analysis

	Functional forms	**Parameters**	**Notes**
Variance of recruitment	$\Omega_t = lnN(\mathrm{M}, \sigma^2)$	$\mathrm{M} = 1$ $0.05 < \sigma^2 < 0.50$	Recruitment is constrained to be greater than zero, lognormally distributed, while we vary the variance and keep the mean constant.
Growth	$\omega_a = (a^\gamma - 1) + 0.3$	$0.25 < \gamma < 0.70$	At the lowest growth parameter (0.25), the weight-at-age

			approximately resembles the U.S. Bering Sea pollock fishery.
Price	$p_a = \beta * \omega_a + 0.45$	$0.10 < \beta < 0.55$	Prices increases linearly with weight, but weight increases at a diminishing rate.
Cost	$c(f_{i,t}) = \alpha * f_{i,t}$	$0.025 < \alpha < 0.250$	Constant per-unit-effort cost, where the fishing mortality $f_{i,t}$ is constrained less than or equal to unity and increases with selectivity.

We solve our model for a number of different types of fisheries, where different fisheries have faster or slower growing fish, and costs of selectivity may be larger or smaller, and show how the magnitude of the selectivity externality changes.

To understand the nature of the externalities and why they occur, we can decompose the change in revenue between the competitive harvesters and the first-best optimal as changes in quantity and prices. When harvesters catch smaller fish, the price per weight they receive on average per fish is smaller, and the value of their catch is smaller (the forgone revenue due to price (red)). However, if they choose to be more selective, they incur greater cost (green and yellow). The harvester maximizes its current-period profits by declining to be more selective. However, by being less selective this changes the age structure of the stock over time. While harvesters internalize the change in price, they do not account for changes in the stock structure because all participating harvesters affect the state variable, and not just the individual harvester.

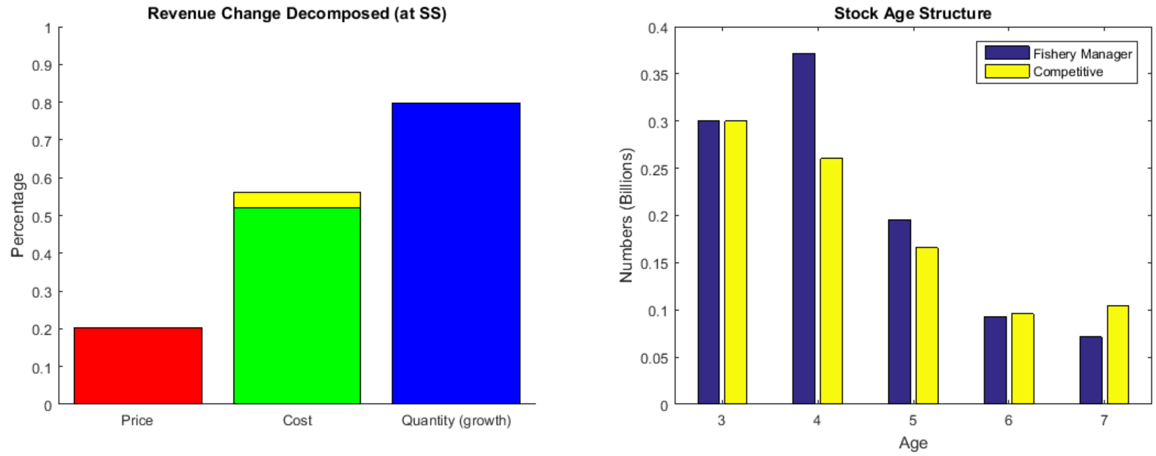

Figure 3.1: Difference between competitive harvesters and fishery manager

The difference in the state (age structure) has two effects: 1) a stock externality or change in revenue due to changes in quantity (blue), and 2) a skewed-structure externality that leaves fewer large fish and increases the cost of targeting larger fish (yellow). The stock externality occurs because catching smaller fish that grow at a faster rate decreases the overall rate of growth of the biomass, and therefore steady state biomass and the quantity of catch allocated to harvesters decreases. The skewed-structure externality results from fewer large fish to catch, which increases the cost and difficult of targeting larger fish. The fishery manager faces a smaller increase in cost from being more selective (green).

For all harvesters, the increase in cost from being more selective (under the optimal selectivity) is less than the increase in revenue (less than 1)[50]. As the cost of selectivity increases, harvesters do not obtain a sufficient increase in value from catching larger fish, as increasing selectivity increases cost and this increase in cost still outweighs their individual increase in price from catching larger fish. Harvesters cannot take advantage of the increase in revenue from quantity or decrease in cost from age structure because the state variable is dependent on the actions of all other harvesters, and not just the decisions of the individual noncooperative harvester.

[50] Recall that being more selective is to select a smaller subset of ages.

3.3 INTERACTIONS

For both noncooperative harvesters, and the fishery manager, as growth and the price premium for larger fish increase, they become more selective, and as cost increases, they become less selective.

Table 3.2: First- and second-order effects on selectivity

Effect on selectivity	**Variance in Recruitment**	**Growth**	**Price**	**Cost**
First order	(0)	(+)	(+)	(-)

Effect of interactions on selectivity (second order)	**Variance in Recruitment**	**Growth**	**Price**	**Cost**
Variance in Recruitment	(0)	(0)	(0)	(0)
Growth	(0)	(-)	(0)	(+)
Price	(0)	(0)	(-)	(+)
Cost	(0)	(+)	(+)	(0)

In Figure 3.2 we show that as cost increases, both competitive harvesters and the fishery manager decrease their selectivity as it becomes more costly to be more selective. However, this effect is decreasing with cost, and as prices increase, the effect is smaller as well; increased prices mitigate the incentive to decrease selectivity, to an extent. Increased growth has a similar mitigation effect; as growth increases, selectivity decreases at a slower rate with cost. When growth is not as fast, the first-order effect from cost is greater (selectivity decreases at a faster rate). We show the signs for both first-order and second-order effects above, and all interactions can be found in the appendix.

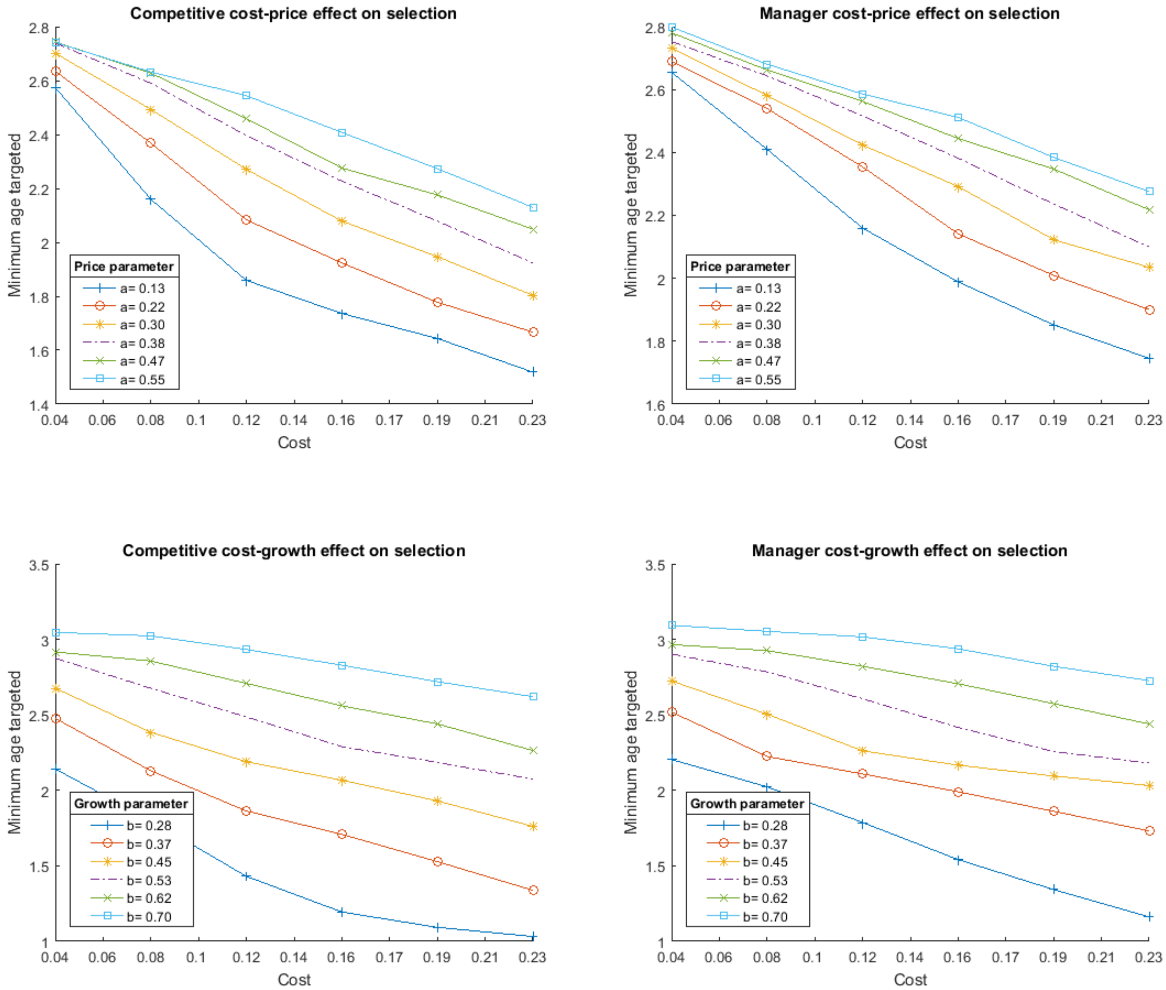

Figure 3.2: Effects of cost and fish growth on selectivity

In Figure 3.3 we show that growth and prices both increase selectivity because as the growth rate increases the forgone benefit from targeting smaller fish increases, while increased prices increase the benefit from being more selective as larger fish are worth more, relative to the increase in cost that would be incurred. These effects are both diminishing with respect to themselves. Notably, variance in recruitment does not have a first- or second- order effect on selectivity. This does not mean that in a given period a harvester would not react to a particularly large age class, but rather it does not affect the harvesters expected value of the fishery (recall the mean of our recruitment function is constant).

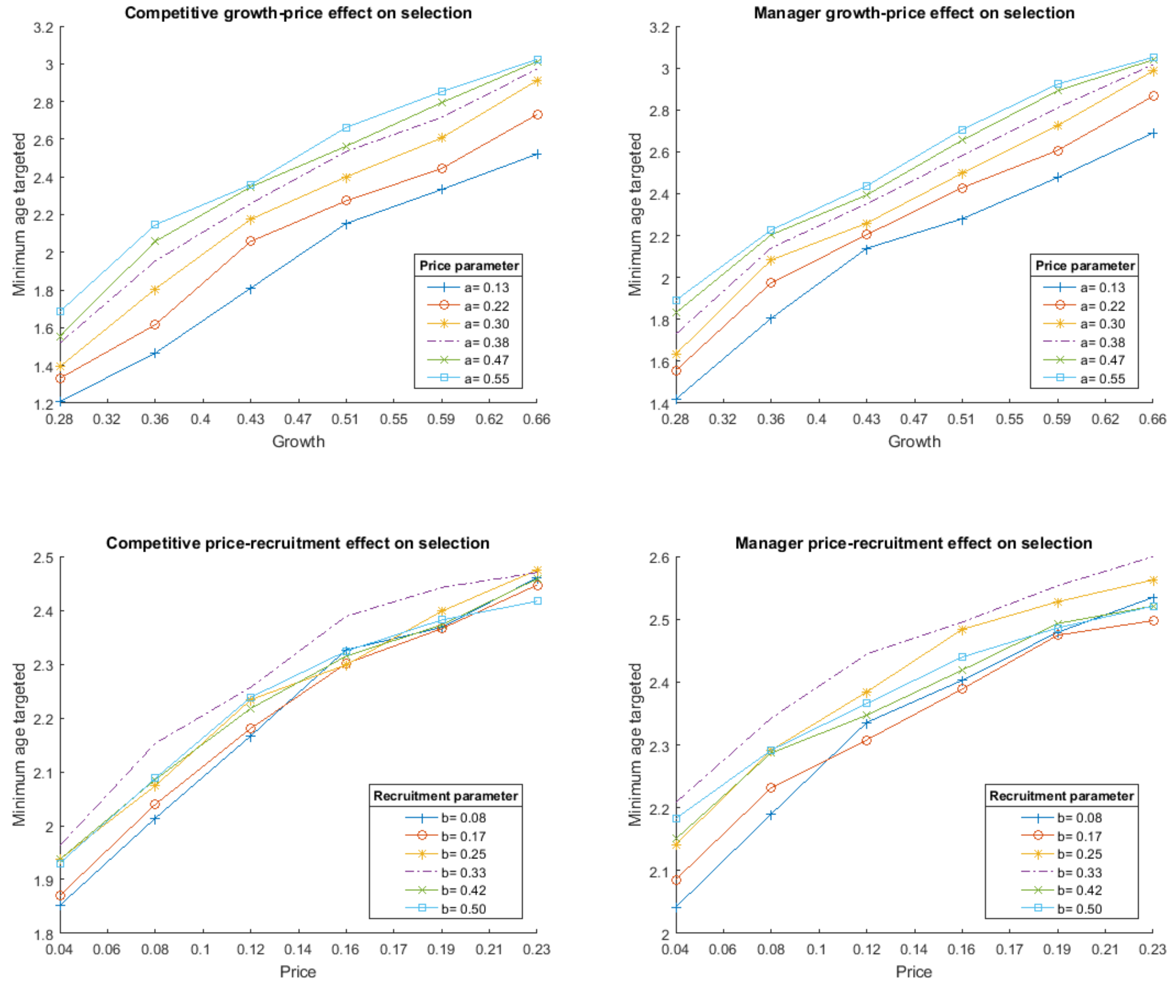

Figure 3.3: Effects of price and recruitment on selectivity

Competitive harvesters react to changes in cost at a faster rate than the fishery manager. For example, decreases in price cause the competitive harvester to decrease selectivity much faster than the fishery manager. Figure 3.4 shows that as per-unit-effort costs (α) increase, the welfare loss from noncooperative harvesting increases because the *difference* in selectivity between the competitive harvester and fishery manager increases. Noncooperative harvesters decrease their selectivity at a faster rate than what a benevolent manager would choose, and this decreases profits both during the transition path and at the steady state.

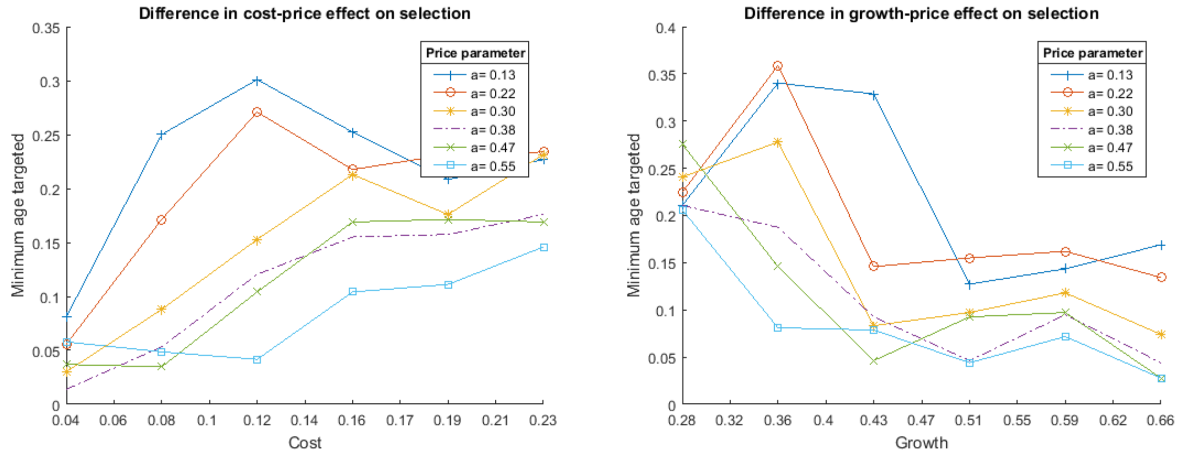

Figure 3.4: Differences in selectivity

As prices and growth increase, the welfare loss from noncooperative harvesting decreases.[51] Higher prices and a greater quantity of larger fish allow noncooperative harvesters to be more selective and the difference in selectivity decreases. Second order effects can be found in the appendix.

Table 3.3: First-order selectivity differences

Effect on selectivity difference between competitive harvesters and fishery manager	**Variance in Recruitment**	**Growth**	**Price**	**Cost**
First order	(0)	(-)	(-)	(+)

3.4 Policy tool

Therefore, we propose a policy tool that allocates additional quota as a function of targeted size. When harvesters target a larger size, the fishery manager offers them additional quota equal to SIF_{it}* *TAC/V*. The stock impact factor is not constant over time, however, but rather changes as a function of age structure at any given period. Because we numerically approximate the dynamic game, we are able to choose the correct policy tool for the approach path to equilibrium. Notably, the magnitude of the first-order effects and even the signs of the second-order effects are not

[51] Because selectivity is lower bounded (they cannot target fish younger than age 3), at low growth and low price the difference becomes smaller as competitive harvesters have already reached the lower bound.

constant across time, but depend on the state of the fishery (total biomass and stock structure). The interactions between growth, cost, and price tend to be larger when the biomass is larger in general and there are more large fish (during the transition period).

We note, the additional revenue due to an increase in quota (Quantity (quota)), combined with the increase price harvesters receive from larger fish (Price), is just slightly greater than the additional cost harvesters would receive from being more selective (Cost). This incentivizes them to target larger fish, where they receive a greater price per weight, catch more fish, and notably, end up with more fish to catch in the future as well. The policy tool depends on the state of the stock. As the proportion of desired targeted biomass decreases, the manager must offer additional quota to compensate, and when the proportion of desired targeted biomass is larger, the manager does not need to offer as much quota. At the steady-state, the manager offers approximately 2.5 percent more quota.

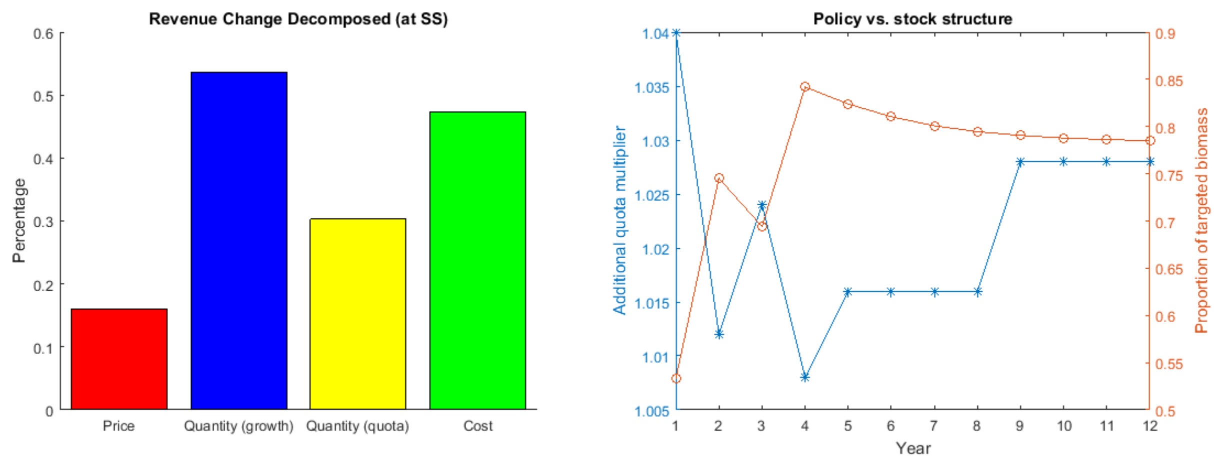

Figure 3.5: Proposed policy tool

Even though harvesters end up harvesting more fish over time, the biomass over time actually increases relative to competitive harvesting. This is because as harvesters target larger fish, the overall rate of growth of the biomass increases, because they are sparing smaller fish that grow at a faster rate. This increase in growth compensates for the increase in quota that harvesters receive from targeting larger fish. Therefore, the policy tool allows harvesters to harvest a greater quantity of fish while maintaining a greater steady-state level of biomass, and the harvester obtains greater prices per weight from their larger fish.

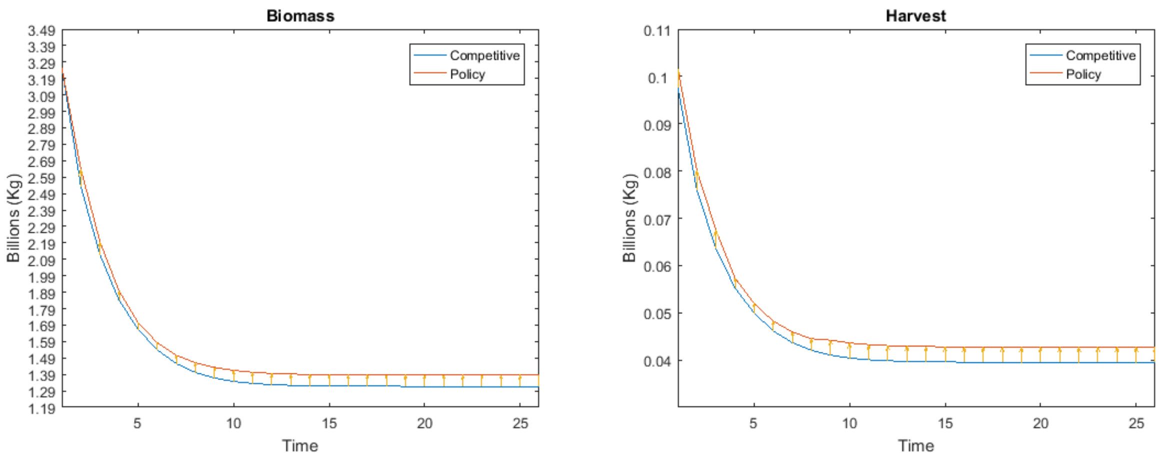

Figure 3.6: Differences in biomass and harvest

3.5 Discussion

We emphasize how the characteristics of a fishery define the magnitude of welfare losses from noncooperative size selective decisions. The approach path holds important implications for policy, as our policy instrument dissuades the noncooperative harvesters from unilaterally decreasing their harvesting costs at the expense of fishery biomass and other fishery participants. We show that the competitive harvesters fish smaller fish to decrease their costs. This imposes an externality on other types of harvesters and future harvesters by changing the distribution of sizes, and decreasing the steady state biomass (and therefore future harvest). As price per weight and growth rate increases, this mitigates the race to fish for smaller fish, to an extent. We propose a policy tool that allocates additional quota when harvesters target larger fish, and show that harvesters can catch more fish that are more valuable per weight, and still result in a larger biomass over time because the increased rate of growth from sparing small fish compensates for larger quotas.

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APPENDIX A

A.1 Full coefficient estimates

Full coefficient estimates are presented in this section. In general own- and cross-price elasticities are the correct signs economic theory would suggest. The seasonal dummy signifies there tends to be more fillet production in the summer Season B.

Overall fit for each group is good, with R^2 values ranging from 0.81 to 0.96. Coefficients from the fillet regression are denoted "d1", the other regression "d2", and surimi "d3". Product own- and cross-price coefficients are denoted "a*xy*", where "x" and "y" are the relevant products (e.g. aFF = fillet own-price, aFS = fillet-surimi cross-price). Starred values indicate significance at a conventional 0.05 level.

Group 1	**beta**	**se**
aFF	0.021*	0.009
aOO	0.001	0.001
aSS	0.008*	0.001
aFO	0.005*	0.001
aFS	0.001	0.001
aOS	0.001*	0.000
d1SeasonB	0.274*	0.006
d1CPUE	0.020*	0.006
d1WPF	0.050*	0.014
d1VAR	-0.003	0.005
d2SeasonB	0.043*	0.004
d2CPUE	0.003	0.003
d2WPF	0.003	0.007
d2VAR	0.005*	0.002
d3SeasonB	0.049*	0.004
d3CPUE	-0.010*	0.004

d3WPF	-0.030*	0.008
d3VAR	0.006*	0.003
aF	0.159*	0.052
aO	0.018	0.023
aS	0.155*	0.026
aCPUE	1.163*	0.301
aWPF	0.160	0.542
aVAR	-0.108	0.175
dCPUE	-0.030	0.044
dWPF	0.171	0.319
dVAR	-0.007*	0.027
dCPUEWPF	-0.056	0.075
dCPUEVAR	0.012	0.024
dWPFVAR	-0.091	0.075
SeasonB	-0.421*	0.019

Group 2	**beta**	**se**
aFF	0.026*	0.004
aOO	0.005*	0.001
aSS	0.133*	0.008
aFO	0.004*	0.001
aFS	-0.031*	0.005
aOS	-0.007*	0.001
d1SeasonB	0.250*	0.009
d1CPUE	-0.007	0.008
d1WPF	0.135*	0.018
d1VAR	-0.008	0.006
d2SeasonB	0.023*	0.005
d2CPUE	0.000	0.004
d2WPF	0.002	0.009

d2VAR	-0.001	0.003
d3SeasonB	0.060*	0.009
d3CPUE	0.019*	0.008
d3WPF	-0.149*	0.018
d3VAR	0.018*	0.006
aF	0.266*	0.067
aO	0.037	0.031
aS	0.079	0.066
aCPUE	0.368	0.325
aWPF	0.641	0.501
aVAR	-0.164	0.179
dCPUE	0.076	0.043
dWPF	-0.453*	0.216
dVAR	-0.044	0.024
dCPUEWPF	-0.044	0.064
dCPUEVAR	0.005	0.022
dWPFVAR	0.103	0.061
SeasonB	-0.360*	0.019

Group 3	**beta**	**se**
aFF	0.010*	0.003
aOO	0.010*	0.002
aSS	0.047*	0.003
aFO	0.013*	0.002
aFS	-0.013*	0.003
aOS	0.000	0.002
d1SeasonB	0.201*	0.005
d1CPUE	0.025*	0.004
d1WPF	0.087*	0.010
d1VAR	0.005	0.003

d2SeasonB	0.041*	0.004
d2CPUE	-0.004	0.003
d2WPF	-0.036*	0.007
d2VAR	0.012*	0.002
d3SeasonB	0.107*	0.006
d3CPUE	-0.006	0.005
d3WPF	-0.102*	0.012
d3VAR	0.014*	0.004
aF	-0.042	0.037
aO	0.125*	0.026
aS	0.414*	0.040
aCPUE	1.026*	0.255
aWPF	0.759	0.428
aVAR	-0.358*	0.144
dCPUE	-0.005	0.034
dWPF	-0.221	0.184
dVAR	-0.048*	0.021
dCPUEWPF	-0.092	0.055
dCPUEVAR	0.035	0.018
dWPFVAR	0.061	0.056
SeasonB	-0.411*	0.017

Group 4	**beta**	**se**
aFF	-0.005*	0.002
aOO	0.001*	0.000
aSS	0.006*	0.001
aFO	-0.003*	0.001
aFS	-0.001	0.002
aOS	0.002*	0.001
d1SeasonB	0.222*	0.010

d1CPUE	-0.008	0.008
d1WPF	0.027	0.018
d1VAR	0.013*	0.005
d2SeasonB	0.029*	0.004
d2CPUE	-0.008*	0.003
d2WPF	-0.008	0.007
d2VAR	0.005*	0.002
d3SeasonB	0.073*	0.009
d3CPUE	0.003	0.006
d3WPF	-0.026	0.014
d3VAR	0.004	0.004
aF	0.065	0.062
aO	0.098*	0.022
aS	0.034	0.049
aCPUE	0.346	0.327
aWPF	1.390*	0.683
aVAR	-0.533*	0.233
dCPUE	0.102*	0.046
dWPF	-0.556	0.292
dVAR	-0.048	0.031
dCPUEWPF	-0.115	0.088
dCPUEVAR	0.071*	0.028
dWPFVAR	0.235*	0.081
SeasonB	-0.282*	0.024

A.2 Modified parameter homogeneity test and Monte Carlo experiment

The parameter homogeneity test of Pesaran and Yamagata compares the slope estimates of individuals to a suitable group estimator. The null hypothesis of the dispersion t test can be written as $H_0\text{: } \theta_{i,Z} = \theta_Z \; \forall \; i$. The notation $\theta_{i,Z}$ denotes a vector of coefficients associated with covariates

Z from the i^{th} harvester we wish to jointly test, such that θ_Z is a suitable pooled estimator of the coefficients.

Because our coefficients of interest are the effects of size on revenue share of each product, we test the subset of size coefficients by partitioning our stacked regression of all revenue share equations. The individual dispersion statistic is then written as:

$$S_i = \sum_i^N (\hat{\theta}_{i,Z} - \hat{\theta}_{WFE,Z})' \frac{M_i Z_i' (S_{OLS}^{-1} \otimes I_{(J+1)T}) M_i Z_i}{\sigma_i^2} (\hat{\theta}_{i,Z} - \hat{\theta}_{WFE,Z}).$$

Because we simultaneously estimate three revenue share equations, we jointly test the effect of size on each revenue share, and our vector of test coefficients $\hat{\theta}_{i,Z}$ is a 1x3 vector of (SUR) estimators for each harvester, using the equation-by-equation ordinary least squares (OLS) residuals for the individual harvester. In addition, we modify the test statistic to take advantage of the cross-equation correlations, where S_{OLS}^{-1} corresponds to the pooled error covariances using equation-by-equation estimates, and $\left(S_{OLS}^{-1} \otimes I_{(J+1)T}\right)$ the Kronecker product of the covariances with an identity matrix with size equal to the number of equations *J*, plus one, times the number of weekly observations *T*. The matrix of (logged) size covariates we wish to test is defined as Z_i which is a (JxT) x 3 matrix with each size covariate corresponding to one of the three given revenue share equations, and we estimate the weighted fixed effects SUR estimator $\hat{\theta}_{WFE,Z}$ by using the single-equation OLS residuals of the pooled sample. Because we have partitioned our regression to estimate the subset of coefficients we are interested in, M_i corresponds to the annihilator matrix of all other covariates not included in Z_i, or $I_T - X_t(X_t' X_t)^{-1} X_t{}'$, where the remaining covariates not tested, including the matrix of vessel fixed effects, is written as X_t.

The variance of the regression uses the pooled SUR estimator $\hat{\theta}_{SUR,Z}$ of our coefficients of interest, as well as the pooled cross-equation error covariance estimates, where y_i is the stacked revenue shares of each harvester:

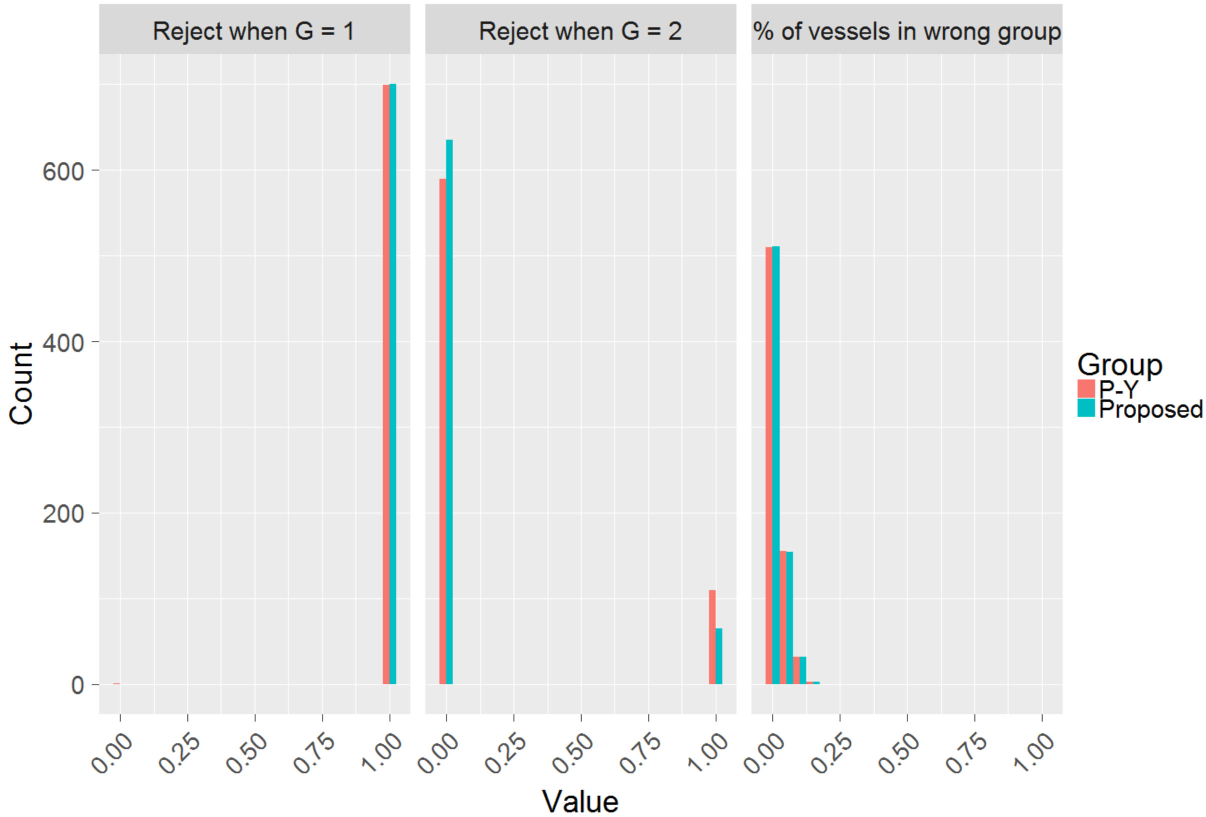
$$\sigma_i^2 = \frac{(M_i y_i - \hat{\theta}_{SUR,Z} M_i Z_i')' (S_{OLS}^{-1} \otimes I_{(J+1)T}) (M_i y_i - \hat{\theta}_{SUR,Z} M_i Z_i')}{JT-1}.$$

Pesaran and Yamagata show that the standardized test statistic for the entire sample is then distributed standard normal:

$$\frac{1}{\sqrt{N}}\sum_{i=1}^{N}\frac{S_i - k}{\sqrt{2k}} \sim N(0,1)$$

For our test statistic that identifies group membership, conditional on a number of groups, we use the variance associated with the test coefficients, using the feasible generalized least squares (FGLS) estimate of the SUR estimator: $(M_i y_i - \hat{\theta}_{SUR,Z} M_i Z_i)'(M_i y_i - \hat{\theta}_{SUR,Z} M_i Z_i)$. The FGLS residuals do not use the cross-equation correlations (Wooldridge 2010).

We use a Monte Carlo experiment to test the efficacy of our modified parameter homogeneity test by comparing its performance to the standard single-equation test statistic. Our data generating process is for N = 20, T = 200, on 700 iterations, where we estimate a system of SUR based on the revenue share equations in the main text: $s_{i,t,j} = \alpha_{i,j} + \sum_{g=1}^{G} \theta_{g,j,Z} \ln(Z_{i,t})\, 1(i \in g) + \Sigma_k \beta_{j,k} \ln(p_{i,t,k}) + \Sigma_m \theta_{j,m} \ln(v_{i,t,m}) + \mu_{i,t,j}$.

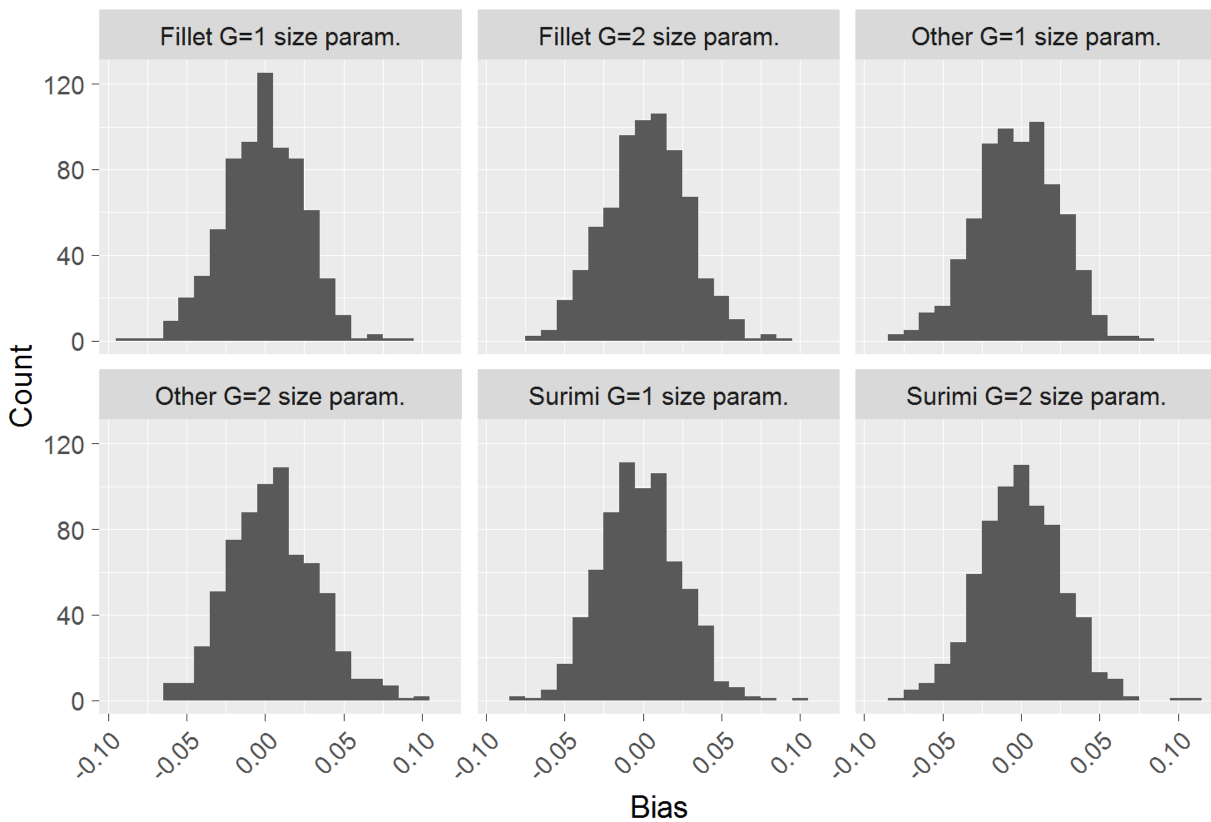


We see that the proposed parameter homogeneity test has improved statistical size over the original Pesaran and Yamagata (P-Y) test in this SUR application; when the true number of groups is 2, the test rejects the null at a frequency of 0.09, while the original test statistic rejects (incorrectly) at a frequency of 0.15. When the estimated number of groups is 1, the test rejects the null at a frequency of 1.00, at a confidence level of 0.05. In addition, the clustering algorithm generally places the vessels in the correct group; the percentage of vessels that are placed in the wrong group, on average, is 0.016.

Test	**P-Y**	**Proposed**
Reject when G = 1	0.99	1.00
Reject when G = 2	0.15	0.09
% of vessels in wrong group	0.01	0.01

Furthermore, the estimated coefficients, compared to the true coefficients, appear unbiased.

Coefficient	1st quartile bias	Mean bias	3rd quartile bias
Fillet G=1	-0.01	-0.00	0.01
Fillet G=2	-0.01	0.00	0.01
Other G=1	-0.01	-0.00	0.01
Other G=2	-0.01	0.00	0.02
Surimi G=1	-0.01	-0.00	0.01
Surimi G=2	-0.01	-0.00	0.01



The unbiasedness of the point estimates also reinforces that the vessels are on average placed in the correct groupings, as incorrect vessel groupings would bias the point estimates because we would be attempting to estimate a single group parameter for a group of vessels with different true parameters.

A.3 Age-structured model

The individual harvester's maximization problem is written as:

$$\max_{s_{i,a,t}} \pi_i = \sum_{t=1}^{\infty}\sum_{a=1}^{A}\left(p_{i,a} * s_{i,a,t} - c\left(f_{i,t}\right)\right)\delta^t$$

$$s.t.\ N_{1,t} = \Omega_t,$$

$$N_{a+1,t+1} = \left(N_{a,t} - \frac{1}{\omega_a}\sum_{i=1}^{V} s_{i,a,t}\right)\mu_t,$$

$$N_{A,t+1} = \left(N_{A-1,t} - \frac{1}{\omega_{A-1}}\sum_{i=1}^{V} s_{i,A-1,t}\right)\mu_t + \left(N_{A,t} - \frac{1}{\omega_A}\sum_{i=1}^{V} s_{i,A,t}\right)\mu_t,$$

$$\sum_{a=1}^{A} s_{i,a,t} \leq \frac{TAC}{V},$$

$$\sum_{i=1}^{V} s_{i,a,t} \leq N_{a,t} * \omega_a$$

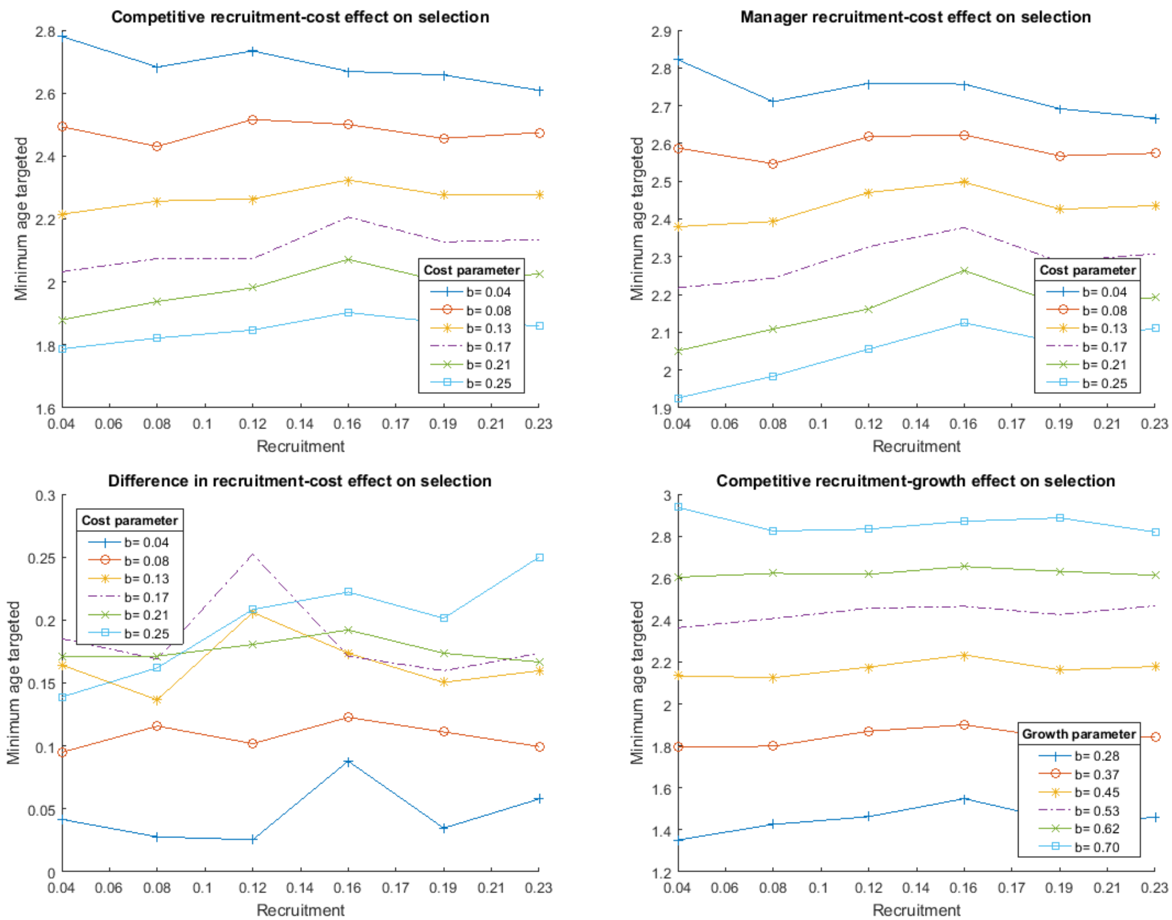
μ_t represents the non-fishing survival rate for each year *t*, while Ω_t represents the number of fish in the youngest age class for each year, or the recruitment. The number of fish in age class *a+1* in the next year equals $N_{a+1,t+1} = \left(N_{a,t} - \frac{1}{\omega_a}\sum_{i=1}^{V} s_{i,a,t}\right)\mu_t$, or the number of fish left at each age after harvest, multiplied by the survival rate. All fish in a single age class are the same size. The number of fish in the largest age class *A* corresponds to all fish greater and including age *A*, or the number of fish aged *A-1* in the last period and all fish in *A* that survived, $N_{A,t+1} = \left(N_{A-1,t} - \frac{1}{\omega_{A-1}}\sum_{i=1}^{V} s_{i,A-1,t}\right)\mu_t + \left(N_{A,t} - \frac{1}{\omega_A}\sum_{i=1}^{V} s_{i,A,t}\right)\mu_t$. The total catch by a single harvester across all ages in a given time period cannot exceed the quota allocated to that harvester, or $\sum_{a=1}^{A} s_{i,a,t} \leq \frac{TAC}{V}$. Finally, harvesters cannot harvest more than exists in an age class, or $\sum_{i=1}^{V} s_{i,a,t} \leq N_{a,t} * \omega_a$.

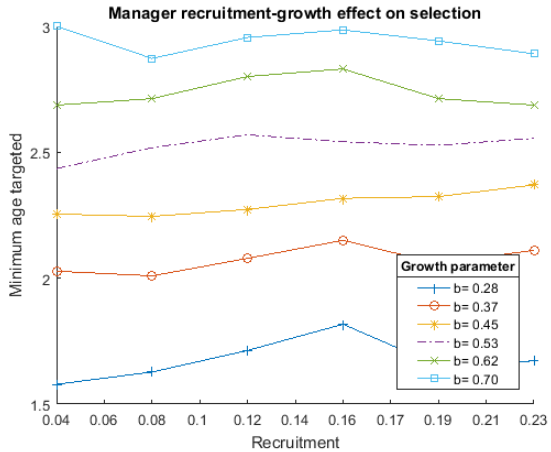
APPENDIX B

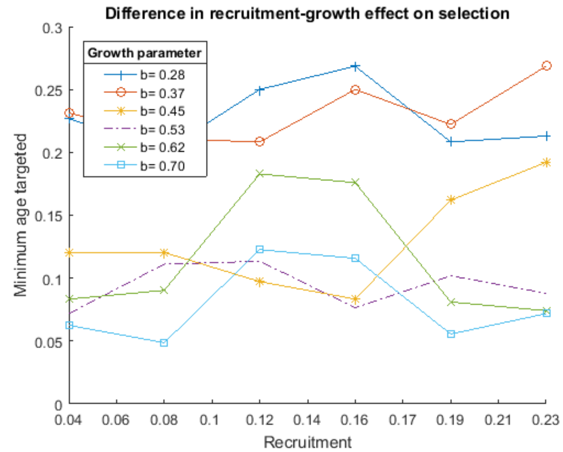
B.1 Effect on selectivity difference between competitive harvesters and fishery manager (second order)

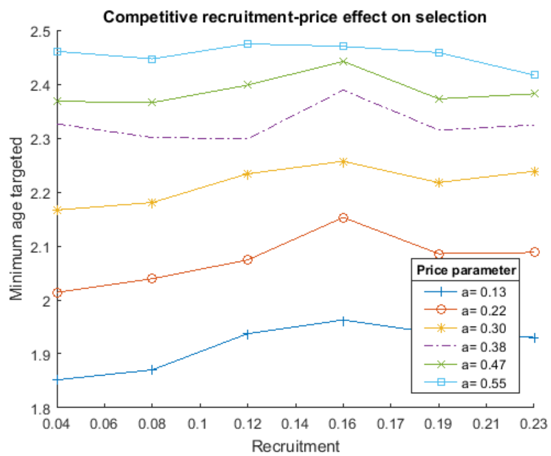
	Variance in Recruitment	**Growth**	**Price**	**Cost**
Variance in Recruitment	(0)	(0)	(0)	(0)
Growth	(0)	(+)	(+)	(-)
Price	(0)	(+)	(+)	(-)
Cost	(0)	(-)	(-)	(0)

B.2 Variance in recruitment

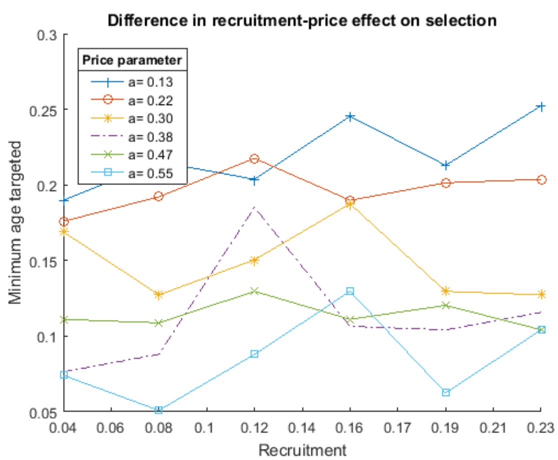



Manager recruitment-growth effect on selection
Minimum age targeted
Recruitment
Growth parameter
b= 0.28
b= 0.37
b= 0.45
b= 0.53
b= 0.62
b= 0.70

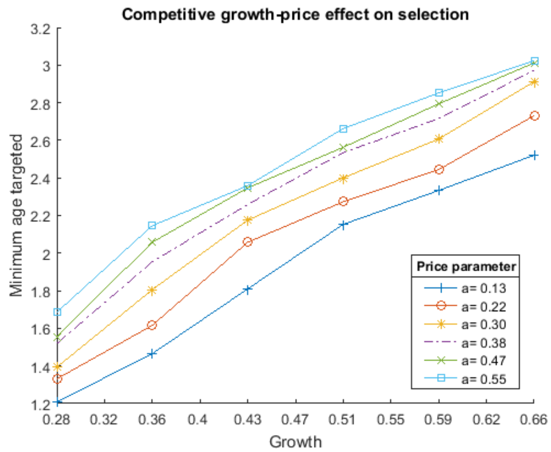

Difference in recruitment-growth effect on selection
Minimum age targeted
Recruitment
Growth parameter
b= 0.28
b= 0.37
b= 0.45
b= 0.53
b= 0.62
b= 0.70


Competitive recruitment-price effect on selection
Minimum age targeted
Recruitment
Price parameter
a= 0.13
a= 0.22
a= 0.30
a= 0.38
a= 0.47
a= 0.55


Manager recruitment-price effect on selection
Minimum age targeted
Recruitment
Price parameter
a= 0.13
a= 0.22
a= 0.30
a= 0.38
a= 0.47
a= 0.55


Difference in recruitment-price effect on selection
Minimum age targeted
Recruitment
Price parameter
a= 0.13
a= 0.22
a= 0.30
a= 0.38
a= 0.47
a= 0.55

B.3 Growth


Competitive growth-price effect on selection
Minimum age targeted
Growth
Price parameter
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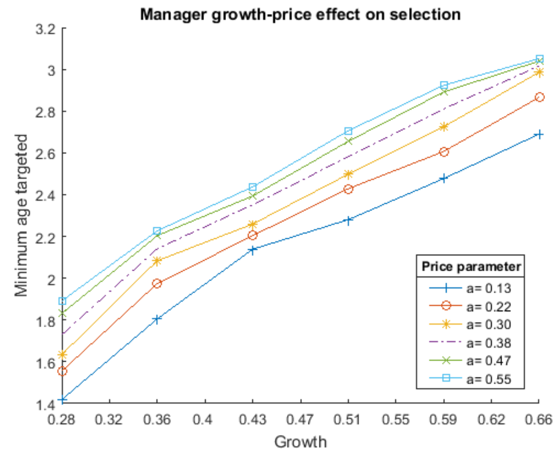
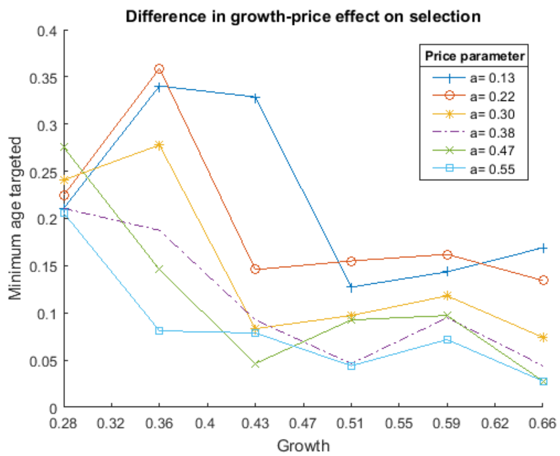
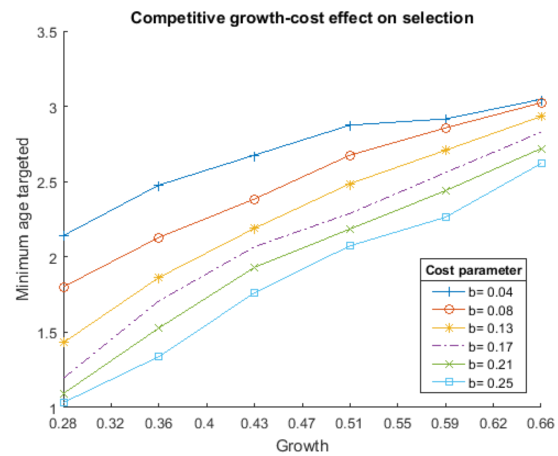
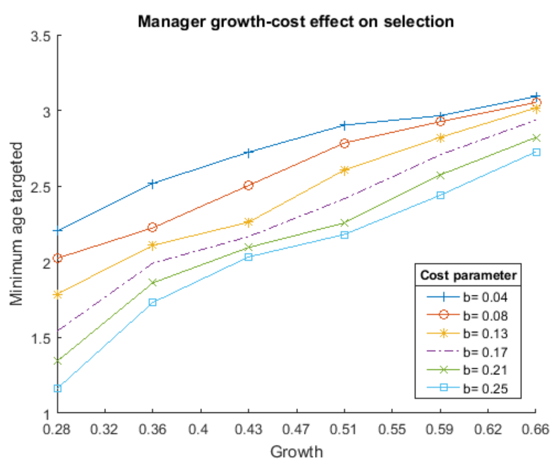
a= 0.22
a= 0.30
a= 0.38
a= 0.47
a= 0.55


Manager growth-price effect on selection
Minimum age targeted
Growth
Price parameter
a= 0.13
a= 0.22
a= 0.30
a= 0.38
a= 0.47
a= 0.55


Difference in growth-price effect on selection
Minimum age targeted
Growth
Price parameter
a= 0.13
a= 0.22
a= 0.30
a= 0.38
a= 0.47
a= 0.55


Competitive growth-cost effect on selection
Minimum age targeted
Growth
Cost parameter
b= 0.04
b= 0.08
b= 0.13
b= 0.17
b= 0.21
b= 0.25


Manager growth-cost effect on selection
Minimum age targeted
Growth
Cost parameter
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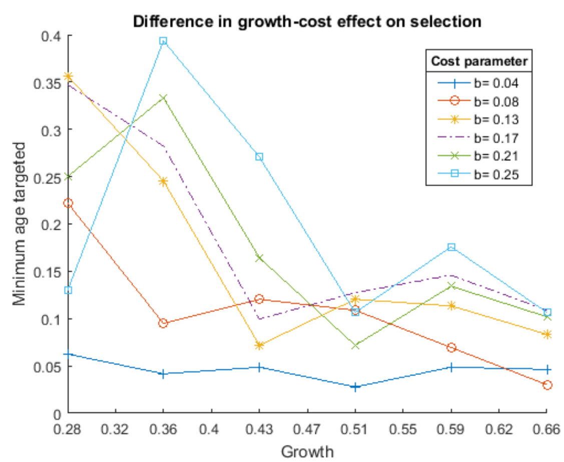
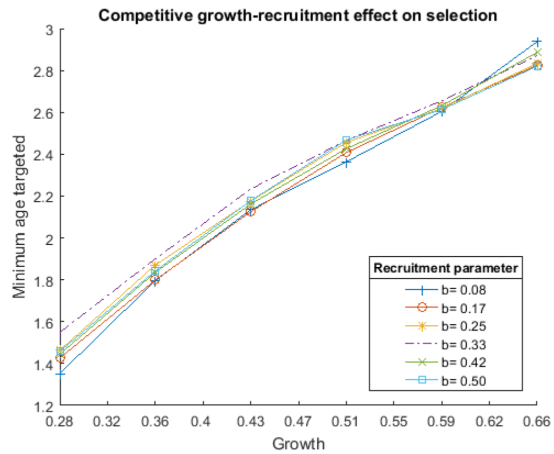
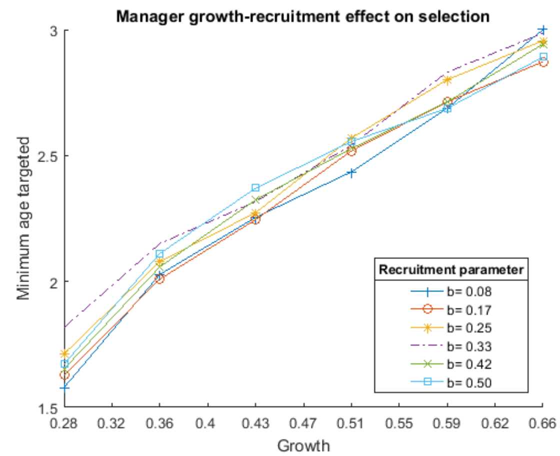
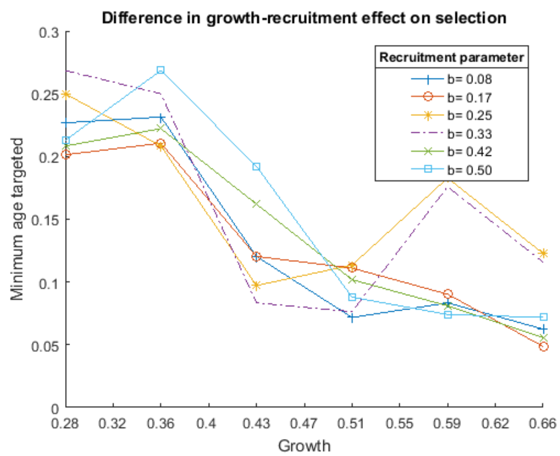
b= 0.08
b= 0.13
b= 0.17
b= 0.21
b= 0.25

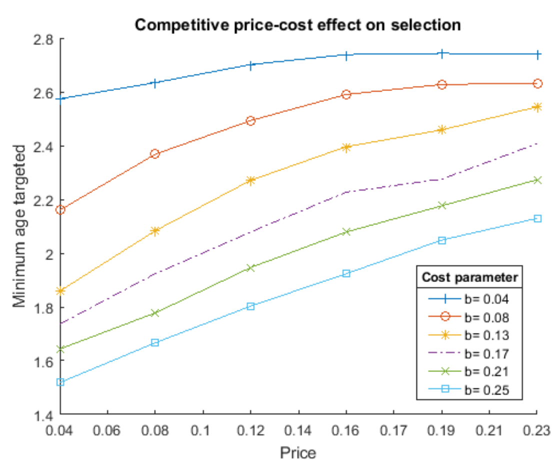

Difference in growth-cost effect on selection
Minimum age targeted
Growth
Cost parameter
b= 0.04
b= 0.08
b= 0.13
b= 0.17
b= 0.21
b= 0.25

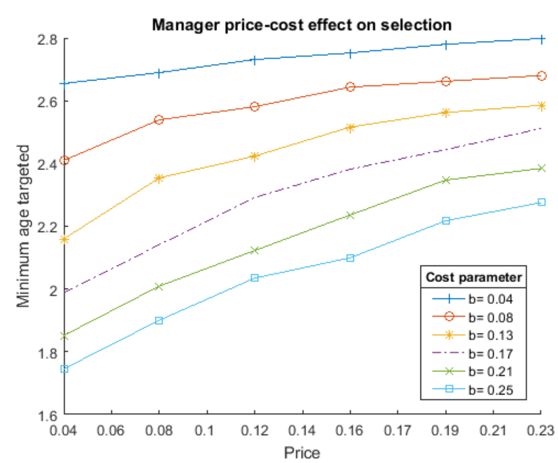

Competitive growth-recruitment effect on selection
Minimum age targeted
Growth
0.28 0.32 0.36 0.4 0.43 0.47 0.51 0.55 0.59 0.62 0.66
1.2 1.4 1.6 1.8 2 2.2 2.4 2.6 2.8 3
Recruitment parameter
b= 0.08
b= 0.17
b= 0.25
b= 0.33
b= 0.42
b= 0.50

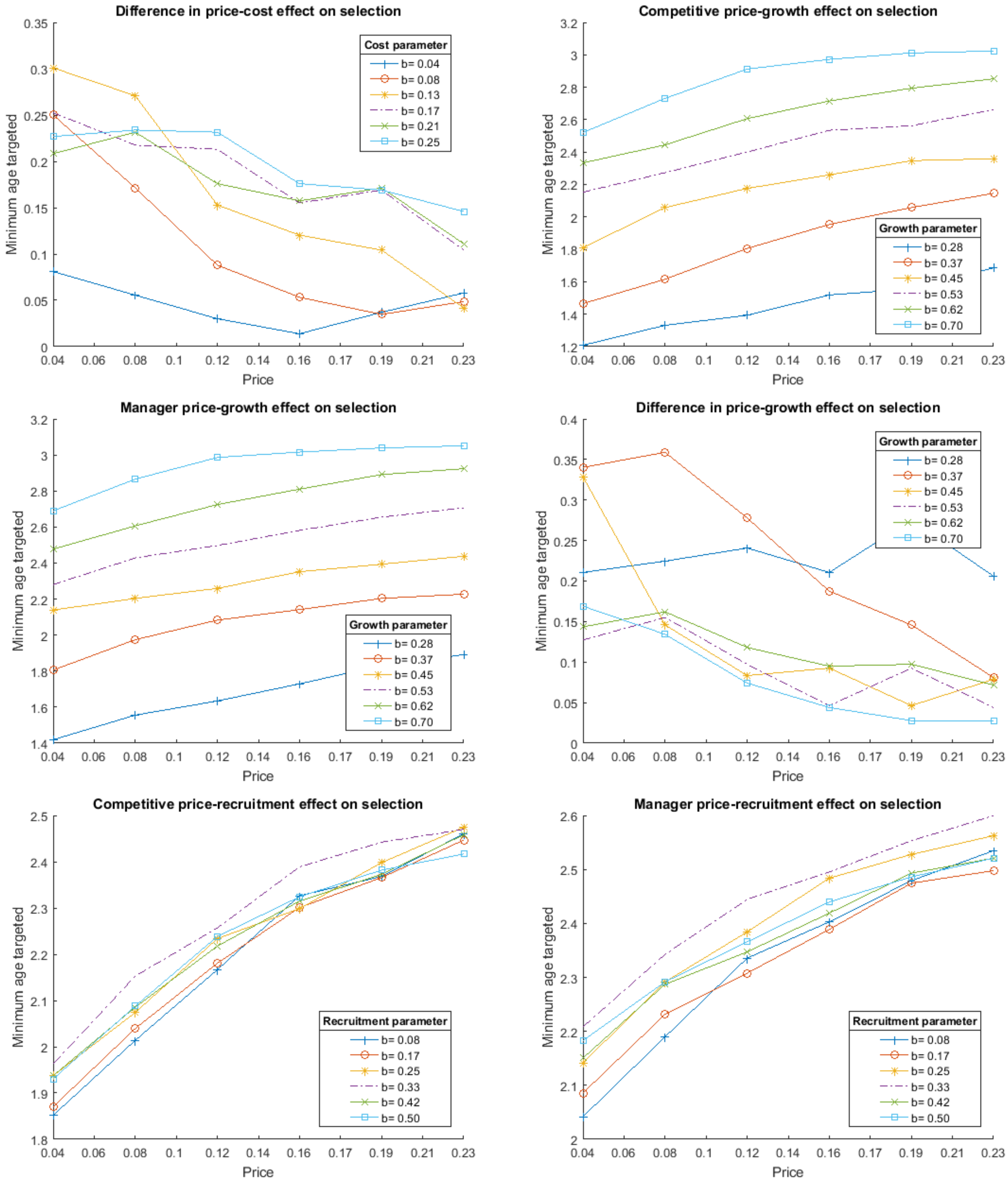

Manager growth-recruitment effect on selection
Minimum age targeted
Growth
0.28 0.32 0.36 0.4 0.43 0.47 0.51 0.55 0.59 0.62 0.66
1.5 2 2.5 3
Recruitment parameter
b= 0.08
b= 0.17
b= 0.25
b= 0.33
b= 0.42
b= 0.50


Difference in growth-recruitment effect on selection
Minimum age targeted
Growth
0.28 0.32 0.36 0.4 0.43 0.47 0.51 0.55 0.59 0.62 0.66
0 0.05 0.1 0.15 0.2 0.25 0.3
Recruitment parameter
b= 0.08
b= 0.17
b= 0.25
b= 0.33
b= 0.42
b= 0.50

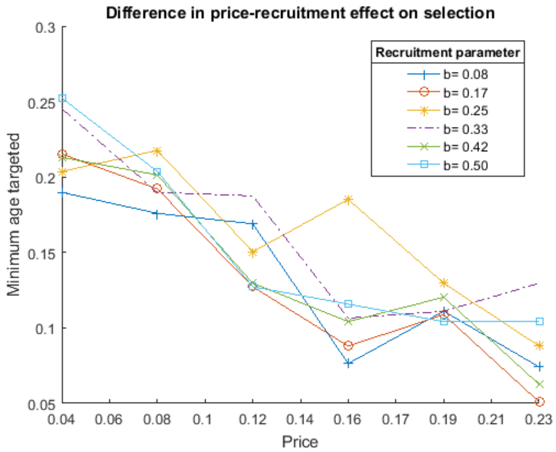
B.4 Price


Competitive price-cost effect on selection
Minimum age targeted
Price
0.04 0.06 0.08 0.1 0.12 0.14 0.16 0.17 0.19 0.21 0.23
1.4 1.6 1.8 2 2.2 2.4 2.6 2.8
Cost parameter
b= 0.04
b= 0.08
b= 0.13
b= 0.17
b= 0.21
b= 0.25


Manager price-cost effect on selection
Minimum age targeted
Price
0.04 0.06 0.08 0.1 0.12 0.14 0.16 0.17 0.19 0.21 0.23
1.6 1.8 2 2.2 2.4 2.6 2.8
Cost parameter
b= 0.04
b= 0.08
b= 0.13
b= 0.17
b= 0.21
b= 0.25



Difference in price-cost effect on selection
Minimum age targeted
Price
Cost parameter
b= 0.04
b= 0.08
b= 0.13
b= 0.17
b= 0.21
b= 0.25
Competitive price-growth effect on selection
Minimum age targeted
Price
Growth parameter
b= 0.28
b= 0.37
b= 0.45
b= 0.53
b= 0.62
b= 0.70
Manager price-growth effect on selection
Minimum age targeted
Price
Growth parameter
b= 0.28
b= 0.37
b= 0.45
b= 0.53
b= 0.62
b= 0.70
Difference in price-growth effect on selection
Minimum age targeted
Price
Growth parameter
b= 0.28
b= 0.37
b= 0.45
b= 0.53
b= 0.62
b= 0.70
Competitive price-recruitment effect on selection
Minimum age targeted
Price
Recruitment parameter
b= 0.08
b= 0.17
b= 0.25
b= 0.33
b= 0.42
b= 0.50
Manager price-recruitment effect on selection
Minimum age targeted
Price
Recruitment parameter
b= 0.08
b= 0.17
b= 0.25
b= 0.33
b= 0.42
b= 0.50


Difference in price-recruitment effect on selection
Recruitment parameter
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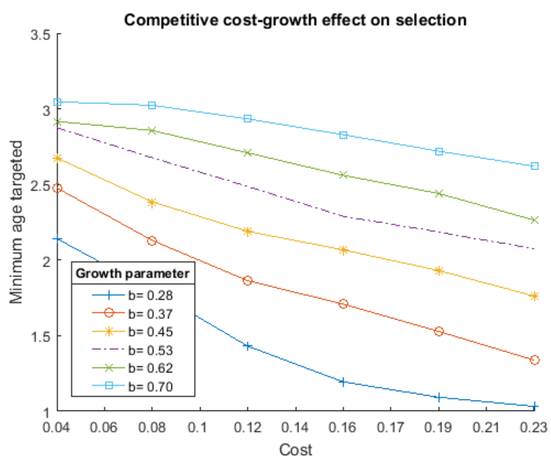
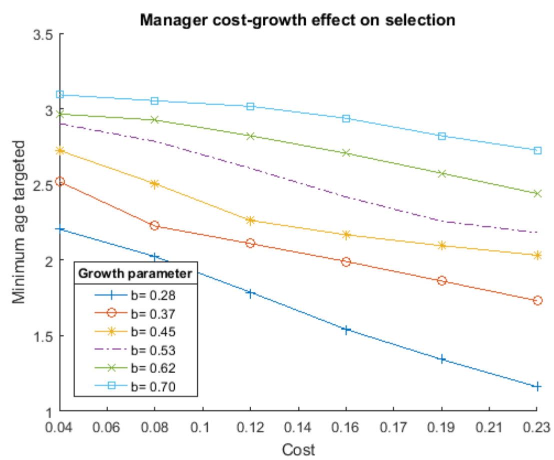
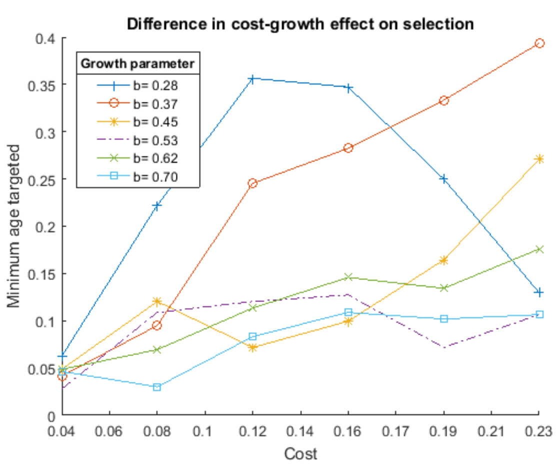
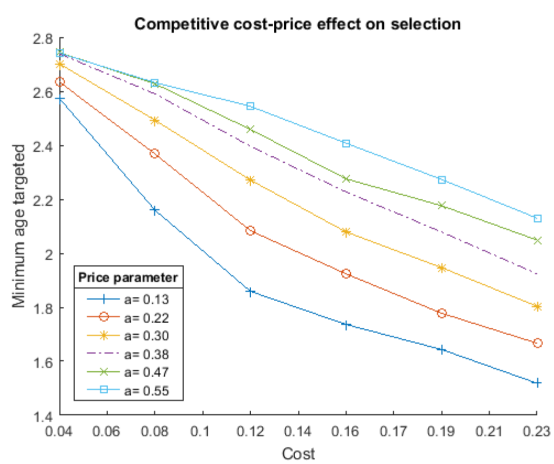
b= 0.17
b= 0.25
b= 0.33
b= 0.42
b= 0.50
Minimum age targeted
Price
0.3
0.25
0.2
0.15
0.1
0.05
0.04
0.06
0.08
0.1
0.12
0.14
0.16
0.17
0.19
0.21
0.23

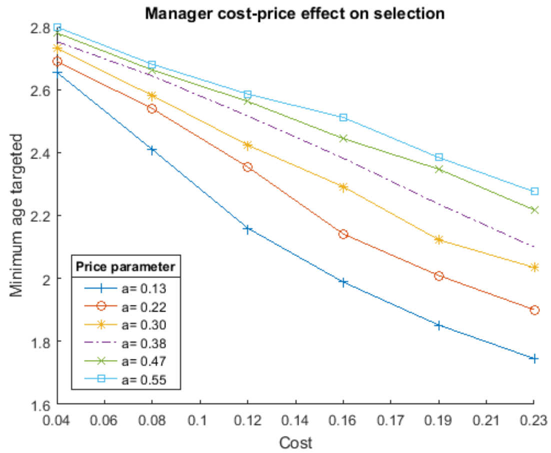
B.5 Cost

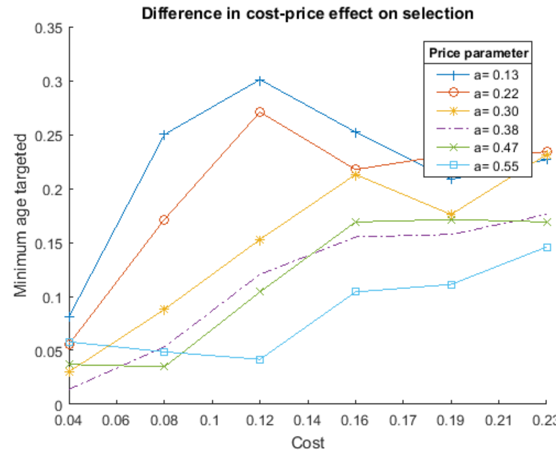

Competitive cost-growth effect on selection
Growth parameter
b= 0.28
b= 0.37
b= 0.45
b= 0.53
b= 0.62
b= 0.70
Minimum age targeted
Cost
3.5
3
2.5
2
1.5
1
0.04
0.06
0.08
0.1
0.12
0.14
0.16
0.17
0.19
0.21
0.23

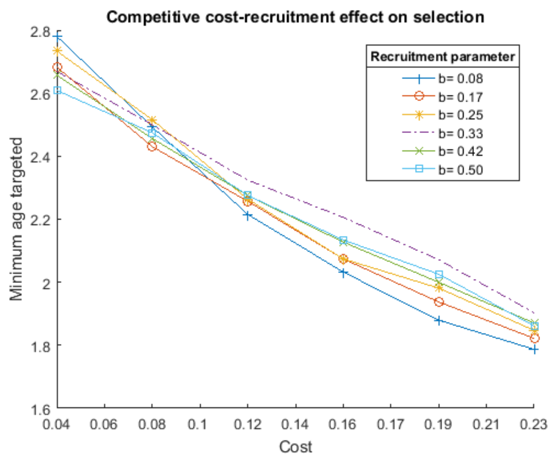

Manager cost-growth effect on selection
Growth parameter
b= 0.28
b= 0.37
b= 0.45
b= 0.53
b= 0.62
b= 0.70
Minimum age targeted
Cost
3.5
3
2.5
2
1.5
1
0.04
0.06
0.08
0.1
0.12
0.14
0.16
0.17
0.19
0.21
0.23

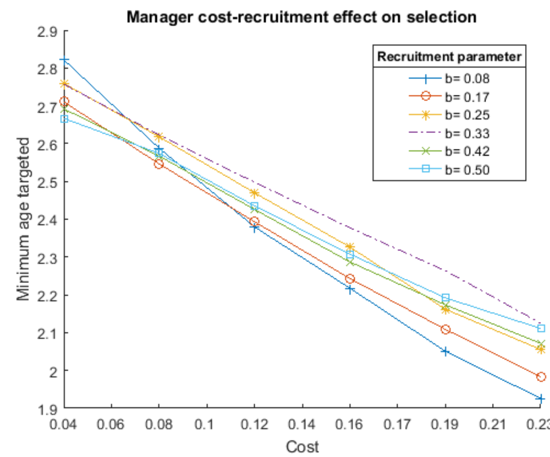

Difference in cost-growth effect on selection
Growth parameter
b= 0.28
b= 0.37
b= 0.45
b= 0.53
b= 0.62
b= 0.70
Minimum age targeted
Cost
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0.04
0.06
0.08
0.1
0.12
0.14
0.16
0.17
0.19
0.21
0.23

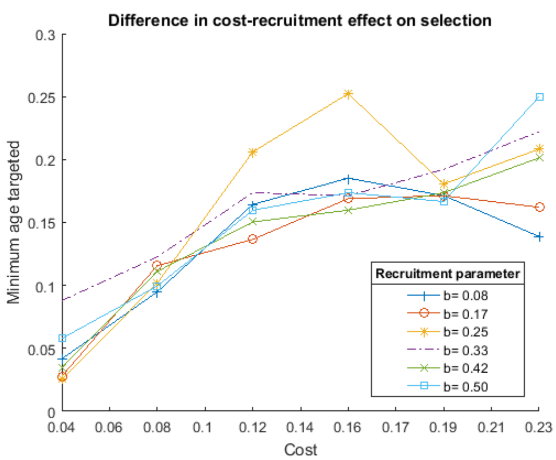

Competitive cost-price effect on selection
Price parameter
a= 0.13
a= 0.22
a= 0.30
a= 0.38
a= 0.47
a= 0.55
Minimum age targeted
Cost
2.8
2.6
2.4
2.2
2
1.8
1.6
1.4
0.04
0.06
0.08
0.1
0.12
0.14
0.16
0.17
0.19
0.21
0.23


Manager cost-price effect on selection
Minimum age targeted
Cost
Price parameter
a= 0.13
a= 0.22
a= 0.30
a= 0.38
a= 0.47
a= 0.55


Difference in cost-price effect on selection
Minimum age targeted
Cost
Price parameter
a= 0.13
a= 0.22
a= 0.30
a= 0.38
a= 0.47
a= 0.55


Competitive cost-recruitment effect on selection
Minimum age targeted
Cost
Recruitment parameter
b= 0.08
b= 0.17
b= 0.25
b= 0.33
b= 0.42
b= 0.50


Manager cost-recruitment effect on selection
Minimum age targeted
Cost
Recruitment parameter
b= 0.08
b= 0.17
b= 0.25
b= 0.33
b= 0.42
b= 0.50


Difference in cost-recruitment effect on selection
Minimum age targeted
Cost
Recruitment parameter
b= 0.08
b= 0.17
b= 0.25
b= 0.33
b= 0.42
b= 0.50