Essays on Bristol Bay Sockeye Salmon Commercial Fishery – Management Policies and Pricing Mechanism

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Abstract

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This dissertation consists of three manuscripts studying management policies and ex-vessel pricing mechanism observed in the world's largest wild sockeye salmon run – Bristol Bay. For the first manuscript, we develop a comprehensive management strategy evaluation technique to evaluate whether increase in the number of fish allowed up each river to spawn (escapement) could improve fishery outcomes for the industry and the region. Our model shows that interannual variance for each district increases as escapements increase, leading to higher mean and variance of fish returns. Since industry is unable to capture greater value during the high-run years while suffering from more frequent low run years, average catch does not necessarily increase. When average value generated is higher relative to the status quo, additional rent is distributed unevenly across harvesters depending how flexible they are in moving between districts. Second manuscript studies the impact of mobility restrictions in relation to area specific run variability that could otherwise be avoided. Using estimated Bristol Bay harvesters daily-district specific production function, we simulate harvester equilibrium behavior for three policies with different degrees of mobility restriction. We find that equilibrium predicted individual harvester catch is the highest under the least mobility restriction (vice versa). We then introduce district-specific stochastic shocks to the run. The policy with the most mobility restriction subjects harvesters to the highest downside risks than the other two policies. The last manuscript studies the post-exchange pricing mechanism observed in the Bristol Bay's ex-vessel pricing market under the experimental setting. The post-exchange pricing mechanism is thought to be inducing processors to behave collusively. We provide an alternative explanation, risk-sharing hypothesis, and test it out using the price-at-exchange pricing mechanism as the empirical benchmark. We find that in the case of certainty, collusion theory may better explain the post-exchange pricing, as supported by the price-at-exchange processors paying on average higher ex-vessel price than the post-exchange processors. However, with introduction of risks, we observe the price-at-exchange processors paying on average lower ex-vessel price than the post-exchange processors, supporting our risk-sharing hypothesis. Furthermore, we find that repeated interaction is key in supporting the post-exchange pricing mechanism.

TABLE OF CONTENTS

List of Figures iii

List of Tables v

Chapter 1. Does More Fish Mean More Money? Evaluating Alternative Escapement Goals in the Bristol Bay Salmon Fishery 1

- 1.1 Introduction 2
- 1.2 Methodology 9
- 1.3 Results 26
- 1.4 Discussion 33

Chapter 2. Mobility Restriction versus Harvesters' Exposure to Run Variability 39

- 2.1 Introduction 39
- 2.2 Data Description 44
- 2.3 Methodology 46
- 2.4 Results 63
- 2.5 Discussion 77

Chapter 3. A Laboratory Evaluation of Post-exchange Pricing as a Mechanism for Risk Sharing 79

- 3.1 Introduction 79
- 3.2 Experiment Design 87
- 3.3 Experiment Results 92

3.4 Discussion 103

Bibliography 106

Appendix A: Additional Tables and Figures for Chapter 1 111

Appendix B: Data souces 113

LIST OF FIGURES

Figure 1.1. Map of Bristol Bay, Alaska 4
Figure 1.2. The modeled relationship between daily catch volume and processed product mix 16
Figure 1.3. Distributions of run size, catch, and wholesale revenues 27
Figure 1.4. Cumulative densities of number of days each district is open to fishing between June 20th and July 17th 31
Figure 1.5. Distributions of ex-vessel revenues 32
Figure 2.1. Daily predicted and actual catch (black line) of Ugashik district for each policy by year in thousands of fish 52
Figure 2.2. Daily predicted and actual catch (black line) of Egegik district for each policy by year in thousands of fish 53
Figure 2.3. Daily predicted and actual catch (black line) of Naknek-Kvichak district for each policy by year in thousands of fish 54
Figure 2.4. Daily predicted and actual catch (black line) of Nushagak district for each policy by year in thousands of fish 55
Figure 2.5. 2010 yearly arrival of fish by district for each simulation with red line being the actual yearly arrival of fish for the district.. 60
Figure 2.6. 2011 yearly arrival of fish by district for each simulation with red line being the actual yearly arrival of fish for the district.. 61
Figure 2.7. 2012 yearly arrival of fish by district for each simulation with red line being the actual yearly arrival of fish for the district.. 62
Figure 2.8. Box plots and histogram of an individual vessel's yearly catch under each policy 66
Figure 2.9. Box plots and histogram of an individual vessel's yearly catch differences between two policies 67
Figure 2.10. Aggregate catch by year and district for all simulations – 2010 and 2011 . 69
Figure 2.11. Aggregate catch by year and district for all simulations – 2012 70

Figure 2.12. Density plot of average yearly catch per vessel across simulations by vessel type 71
Figure 2.13. Density plot of average semi-variance per vessel across simulations by vessel type 75
Figure 3.1. Timeline of a period for three pricing mechanisms....................................... 91
Figure 3.2. Average ex-vessel price by mechanisms and forecast levels under two conditions 94
Figure 3.3. Average harvester participation per session by mechanisms and forecast levels under two conditions 96
Figure 3.4. Average ex-vessel prices paid under the price-at-exchange relative to the post-exchange pricing under different regression methodologies 99
Figure 3.5. Average ex-vessel prices paid under the one-shot game relative to the repeated post-exchange pricing under different regression methodologies 99
Figure 3.6. Coefficient value for number of harvesters participating under regression #4 to #7 103
Figure A.1. Cumulative number of simulated years which a given sub-district was opened for a specified number of days during the period June 20th to July 17th 112
Figure A.2. Distributions of ex-vessel revenues from the Nushagak district under three escapement goal policies across 1,000 simulations of final 74 years each............. 112

LIST OF TABLES

Table 1.1. Bristol Bay Fishery Summary Statistics 5
Table 1.2 Midpoint escapement targets in thousands of sockeye, for the three alternative management strategies 5
Table 1.3 Calibrated Parameters for Relationship between Daily Volume and Product Mix 17
Table 1.4 Coefficient estimates and summary statistics for model equations 21
Table 1.5 Average number of days-on-limits at a range of increases in daily processing capacity 26
Table 1.6 Summary statistics from forward simulations 28
Table 1.7 Percent of years when catches were less than 5, 10, and 15 million fish, Bay wide, across three escapement goal policies... 33
Table 2.1 Coefficient values for each district's production functions and relevant statistics49
Table 2.2 Homesteader district choices by year 50
Table 2.3 District Choices for the 48-hour policy with starting district in Ugashik and Egegik 57
Table 2.4 District Choices for the 48-hour policy with starting district in Nak-Kvi and Nushagak 58
Table 2.5 Annual predicted catch and district assignment difference with different initial allocation assignment process... 59
Table 2.6 Sample statistics of simulated arrival by year (in thousands of fish) 63
Table 2.7 The mean daily catch difference between two policies in a district 64
Table 2.8 Aggregate catch by district in thousands of fish from simulation and actual catch 64
Table 2.9 Yearly aggregate catch % difference by district relative to the actual catch.... 65
Table 2.10 Average vessel yearly catch under each policy and catch differences between two policies in number of fish 68

Table 2.11 Average vessel yearly catch across all simulations under each policy and catch differences between two policies in number of fish 72

Table 2.12 Summary statistics of average catch across all simulation by policy and vessel type and quantile of horsepower for homesteaders versus non-homesteaders 73

Table 2.13 Regression analysis report 76

Table 3.1. Wage schedule based on conditions, forecast/realized wholesale prices under each condition 89

Table 3.2. Processing cost schedule... 89

Table 3.3. Summary Statistics by forecast levels, conditions, and pricing mechanisms .. 93

Table 3.4. Regression analysis results with ex-vessel price as the dependent variable.... 98

Table 3.5. Regression analysis results with ex-vessel price as the dependent variable with different periods dropped... 101

Table 3.6. Average ex-vessel prices paid under price-at-exchange and one-shot post-exchange pricing relative to the post-exchange pricing mechanism for each regression result102

Table A.1. Average age composition proportions used to allocate recruitment across age classes 111

Table A.2. Matrix of harvest rate by fishing option and population (hf, p) for the west side of Bristol Bay 111

Table A.3. Matrix of harvest rate by fishing option and population (hf, p) for the east side of Bristol Bay 111

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DEDICATION

to my parents and brother

Chapter 1. DOES MORE FISH MEAN MORE MONEY? EVALUATING ALTERNATIVE ESCAPEMENT GOALS IN THE BRISTOL BAY SALMON FISHERY

Abstract

We develop an economically sophisticated management strategy evaluation (MSE) for four sockeye salmon fishing districts in Bristol Bay, Alaska, to evaluate whether proposed increases in escapement goals—the number of fish allowed up each river to spawn—could improve fishery outcomes for the industry and the region. Higher escapements increase average runs toward biological MSY, but this is driven by infrequent years of very abundant runs. Our economic model shows processors do not add capacity in response to infrequent abundant runs. Therefore, interannual variance in district-specific catch increases because years with little or no fishing become more frequent to meet higher escapement in low-run years, but industry cannot capture greater value in the high-run years. In abundant runs, processors shift available labor to focus on high-volume, lower-margin products; in very abundant years, insufficient processing capacity allows additional fish to escape. Mobile drift-net vessels that can move to rivers experiencing high runs each year benefit, but district specialists in the small boat and set-net fleets are more vulnerable to years with little or no catch.

1.1 INTRODUCTION

The sockeye salmon (*Onchorhynchus nerka*) fishery in Bristol Bay, Alaska, illustrates how economic and biological objectives can lead to different harvest policy recommendations. Despite its decades-long biological success, the salmon industry in Bristol Bay has experienced a period of economic losses in the most recent decade, prompting some to deem it a biological success but an economic failure (Hilborn 2006), and others to explore opportunities to improve the economic performance of the fishery (Link et al. 2003; Schelle 2004; Bue et al. 2008). Fishery scientists, economists, and many in the fishing industry have long recognized that economic performance of the Bristol Bay salmon fishery may not be optimized at maximum sustainable yield (MSY) levels; quantifying and conveying this has been a challenge. Management Strategy Evaluation (MSE) techniques are being increasingly applied to help stakeholders and managers understand how variability and uncertainty affect the evolution of stock levels and anticipated **biological** yield under different harvest policies. As the approach matures, best practices are being developed to guide the design of MSEs (e.g., Punt et al. 2016), with an emphasis on common sources of data, stock structure and stock parameter uncertainty. We build on this work by developing an economically integrated MSE and use Bristol Bay salmon to identify fishery characteristics that warrant incorporating economic responses within MSEs to ensure economic objectives can be addressed alongside biological objectives, and comprehensive advice can be conveyed to fishery managers and other stakeholders.

Over the course of six weeks each summer, an average of 37 million sockeye salmon return to the five fishing districts in Bristol Bay, Alaska, supporting the most valuable wild commercial salmon fishery in the world. Up to 1500 driftnet vessels, with crews of up to four, jockey for the position on each tide in which the Alaska Department of Fish and Game (ADF&G) declares the fishery to be open. They are joined by up to 900 shore-based set-net harvesting operations, who fish from pre-specified riverside sites. Combined, this $400 million-dollar fishery provides essential food, jobs and economic activity in this isolated region of 6,000 residents (Knapp et al. 2013).

The stocks exploited by this fishery spawn in nine rivers, and are harvested in five single or mixed-stock terminal fishing districts (Figure 1.1). Table 1.1 shows how each commercial fishing district contributes to the total run size, and how run sizes fluctuate. To ensure sustainability, ADF&G establishes escapement goals—a desired range in the number of fish escaping capture in the commercial fishery and returning to the spawning grounds of each river—and permits fishing in the district at the mouth of each river only when escapement is at or above the historic arrival pace that supports meeting those escapement objectives. While larger escapements in most rivers are associated with higher expected future returns, historical observations at higher levels over the last 120 years are infrequent and outcomes ambiguous. This variability is reflected in the precautionary nature of the status quo escapement goals, labeled Current Sustainable Escapement Goals (SEG) line in Table 1.2 (Bakers et al. 2009). Escapement is carefully tracked within the season at enumeration sites (counting towers or fixed sonar sites) on each river, and the number of landed fish is estimated on a daily basis from the observed weight of the catch, the Bristol Bay salmon fishery is perhaps the most intensively managed fishery in the world. It is Marine Stewardship Council certified.

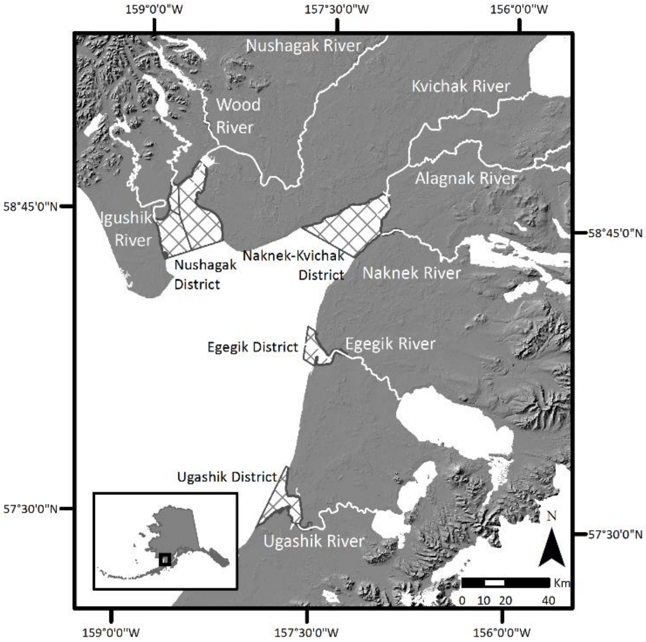


Figure 1.1. Map of Bristol Bay, Alaska

Crosshatched areas describe boundaries of terminal fishing districts, and gray labels indicate river systems of origin for each stock. Map created with shape files from the Alaska Department of Fish and Game Anadromous Waters Catalogue, and U.S. Geological Survey National Hydrography Dataset and National Elevation Dataset. This figure was recreated from Cunningham et al. (2017). The Togiak River and associated terminal fishing district is not pictured and lies to the west of the Igushik River.

As part of an every-three-year review process using the latest stock-recruit data, Fair et al. (2012) suggested that raising the escapement goals—considerably for Egegik and Ugashik—to the Biological Escapement Goals (BEGs) in Table 1.2, would increase yield from the fishery. Harvest achieved by targeting these BEGs was expected to more closely reflect maximum sustainable yield (MSY). Alaska's Policy for the Management of Sustainable Salmon Fisheries specifies that, to the extent possible, salmon fisheries are to be managed for MSY, which depends on sufficient historical stock-recruit data to define MSY escapement. (5 AAC 39.222).

Table 1.1. Bristol Bay Fishery Summary Statistics

	Ugashik District	Egegik District	Naknek-Kvichak District	Nushagak District	Togiak District	Bay-wide
Average Run Size (000) 1980 - 2012	3,919	8,769	16,210	7,442	706	37,046
Standard Deviation	1,593	4,320	8,145	2,944	270	
Average Catch (000) 1980 - 2012	2,752	7,446	8,891	4,936	501	24,526
Standard Deviation	1,396	4,139	5,188	2,271	213	
Average Escapement (000) 1980 - 2012	1,167	1,322	7,319	2,506	205	12,520
Standard Deviation	633	428	4,394	1,222	77	
Average Driftnet Vessels* 2002 - 2012	-	-	-	-	-	1385
Average Driftnet Permits 2002 - 2012	354	552	696	555	110	-

* Permits are required to register to fish in a particular district, but starting in 2004, vessels could fish with two permits and extend their net length from 150 to 200 fathoms, thus the number of vessels fishing in a district each year is not precisely known.

Table 1.2 Midpoint escapement targets in thousands of sockeye, for the three alternative management strategies

District	**Stock**	**Current SEG**	**Proposed SEG**	**BEG**
Nushagak	Igushik	225	300	291
	Wood	1100	1300	1550
	Nushagak	590	700	801
Naknek-Kvichak	Kvichak*	2000	2000	2000
	Alagnak	320	320	320
	Naknek	1100	1450	1858
Egegik	Egegik	1100	1450	5242
Ugashik	Ugashik	850	1000	2602

The Kvichak and Alagnak escapement targets are the same across three scenarios because these systems are not managed separately and targets did not vary across scenarios.

MSY is intuitively linked to good outcomes for harvesters and communities because greater fish availability means more fish to sell, and therefore more fishing income and jobs. In addition, the higher escapement levels necessary to achieve MSY may provide alternative benefits to freshwater ecosystems and salmon-dependent predator communities (Levi et al., 2012).

However, industry, and local communities that depend on low catch variance and tax revenue, have resisted this increase, and encouraged more caution and incremental adjustments to escapement goals. In this highly variable fishery, increasing escapement goals has the potential to result in two side effects of questionable desirability from the perspective of the fishery revenue. First, a potential increase in the frequency of low run years in which less (or no) harvest will be allowed to achieve the higher escapement targets. Low run years are relatively frequent, and times of no harvest are devastating to rural Alaska communities who are heavily dependent on salmon revenue. Second, there will be slightly more frequent very high run years. From a management perspective, the theoretical yield under the escapement goals proposed by Fair et al. (2012) would represent a huge potential harvest, but the fishery lacks the capacity to process potential catches during recent years of high runs. Therefore, many in the industry see increased escapement goals as increasing vulnerability in exchange for larger average runs that provide little or no upside for fishery participants. ADF&G thus proposed a more modest change, the Proposed SEG line in Table 1.2. Bue et al. (2008) showed that economic profitability was influenced by limits on processing and harvesting capacity, and industry intuitively understood that bigger runs do not translate directly into greater economic performance.

Industry responded to Fair et al.'s (2012) proposal by convincing regulators to first examine the economic impacts of moving from the existing goals to four alternatives, three of which are listed in Table 1.2, before revising the escapement goals. Industry was provided two years to work with together with ADF&G and other scientists and recommend escapement goals that take into account the economics of the fishery. To ensure meaningful inputs to our models and realistic alternative escapement goal policies to examine, the study team was guided by a 9-person

Advisory Panel (AP) of individuals with expertise in Bristol Bay fishery management, harvesting and processing, and the regulatory process.

Whether increasing (average) run size in accordance with MSY aligns with the goals of supporting the harvesters and communities that participate in this fishery depends on the industry's ability to catch and process during very large run years (Bue et al. 2008). Current bay-wide processing capacity is around 1.8 million fish per day. Since salmon is landed fresh and cannot be held for long without processing, a day of high catches has two consequences for processors. First, they must curtail the flow of fish coming to their plants by placing their contracted fleets "on limits", declaring that they will not buy more than a fixed number pounds from each vessel during an opening. Additional fish returning during this period escape, but provide no value to the fishing industry in the current year. Limits are not popular among the fleet, and processors that are more frequently forced to put their fishermen on limits have a harder time contracting vessels to their fleet in the future. Nevertheless, limits are clearly part of the processors' strategy for handling considerable inter-annual volatility: they could build plants to accommodate the maximum run size, but instead there is a persistent pattern of at least two days on limits, in roughly two of every five years. This suggests that the value of these additional fish that could be captured during limited periods is not sufficient to cover the cost of maintaining excess processing capacity in the remaining three-of-five years.

The second way processors handle daily gluts is by accelerating their processing rates. If input markets were fluid, the plants would hire temporary labor and purchase other inputs to deal with the high availability of fish. However, because Bristol Bay is geographically isolated, plants must commit to staffing and stocking levels based on preseason run size forecasts, supplied by ADF&G and the University of Washington (UW-FRI). Physical inputs are barged to the region in spring, and laborers are flown up before the season; additional supplies of neither can be accessed on a relevant timeline once the actual extent of the fish run is realized. Instead, processors accelerate fish utilization by redeploying labor onto product lines that can process more fish per effort hour, from labor-intensive fillet lines to head-and-gut or canning lines. These products, particularly if produced in large quantity during a season, are generally lower margin than more labor-intensive products. Thus, product composition depends on the observed run size and timing, so processors cannot project the markets into which they will be selling, and thus the prices they will receive per pound of landed fish.

The bioeconomic picture of Bristol Bay is a complex one, where the value of the catch is limited by available fish in low-run years, but also by processing capacity in high run years. The value of fish on peak run days is eroded through processing into lower value products; in the highest run years, this value is entirely dissipated because capacity constraints allow it to escape. As a result, increases in average run size that also increase the variance of potential catch may not result in more fish being landed and processed, leading some authors to suggest a constant harvest management strategy (Steiner et al. 2011). Further, increasing catch variability is not distributionally neutral because, while individual-river variability can be mitigated by switching to other rivers during the season, harvesters differ in their ability to do this. State-of-the-art driftnet vessels can easily move among river systems to those with more returns, but “homesteaders” who traditionally fish only one district and set-net harvesters generally cannot.

Understanding how three proposed escapement goal policies attain economic and community objectives for the fishery therefore requires not only modeling the stock, but also how participants in the harvest and post-harvest sectors react to run size variability. Harvests, and thus stock size and fishery benefits, will be based on processors’ long-run plant scale choices, which will dictate the size of the work force chosen operate the lines they can keep busy most days of the season, and in turn constrain the product mix, which is determined by the shape and timing of the run as much as its size. This paper describes an integrated bioeconomic management strategy evaluation (MSE) that quantifies the tradeoff between the average yield and the variance in yield, which provided regulators with guidance on designing harvest policies for environments where production variability is a major factor in shaping outcomes for industry and fishing communities.

1.2 METHODOLOGY

Our management strategy evaluation builds upon models of four key processes. First, we describe the age-structured stock-recruit model, which uses historical data to specify the relationship between escapement and subsequent returns of sockeye in future years. This recruitment model interacts with a management model that simulates managers' decisions of which rivers to open and when, based on the available in-season information; this relates intended escapement goals to predicted escapement, capturing management imprecision. Second, we model processors' production decisions, on three timelines: the long run choice of plant scale; the pre-season choice of staffing level, based on run size forecasts; and the daily choice of product form, based on daily landings. Third, we model the annual price flexibility of the dominant salmon products produced in Bristol Bay. Finally, we link processor revenue and product mix to a division of revenue between processors and harvesters. These models are then used as the basis for 100-year forward simulations of the stock and processing industry, to project the mean and variance of fishery revenues to key participants under the alternative escapement goal policies.

Stock-Recruit Model

We use the biological MSE framework developed in Cunningham et. al (2015b) to model daily catch, escapement, and run size for eight major sockeye stocks in Bristol Bay: the Alagnak, Kvichak, and Naknek stocks in the Naknek-Kvichak district; the Wood, Nushagak, and Igushik stocks in the Nushagak district; and the Egegik and Ugashik stocks in their eponymous districts. Here we briefly summarize the key features of the model.

To simulate the spawner-recruit dynamics for each of the river system, Ricker-type spawner-recruit models are fit to data reconstructed by Cunningham et al. (2017) for years 1963 – 2013 (equation 1.1). The expected recruitment, $R_{y,p}$, of each stock from brood year y and stock p is parameterized with $\alpha_{y,p}$, the maximum productivity in the absence of density-dependent compensation, $\beta_{y,p}$, the equilibrium biomass, and $\sigma_{y,p}$, the standard deviation of log-normally distributed process uncertainty.

$$\begin{aligned} R_{y,p} &= S_{y,p} * \exp\left(\alpha_{y,p} \left[1 - \frac{S_{y,p}}{\beta_{y,p}} \right] \right) * \exp\left(\varepsilon_{y,p} \right) \\ \varepsilon_{y,p} &\sim N\left(0, \sigma_{y,p} \right) \end{aligned} \tag{1.1}$$

Three versions of the Ricker model are used to simulate future recruitment patterns for Bristol Bay stocks. The first assumes production dynamics are best approximated by two Ricker functions representing high and low production regimes, where regime transitions are treated as a 1st order Markov process and regime transition probabilities are estimated for each stock using Bayesian methods. This model is used to simulate the recruitment process for the Kvichak, Naknek, Egegik, Ugashik, Wood, and Igushik stocks. Second, a Bayesian Ricker model, assuming a single production regime, is used to simulate the recruitment process for the Alagnak stock. Lastly, a maximum likelihood Ricker model is adopted for the Nushagak stock, given the absence of suitable prior information on equilibrium (unfished biomass); see Cunningham et al. (2015b) for further detail.

Annual abundance levels for each of the four main harvested age classes, $a \in \{1.2,1.3,2.2,2.3\}$,where $a.b$ denotes a fish that spent a years in fresh water before spending b years at sea before returning to spawn. Each of the eight populations are simulated from 2014-2113. The observed escapements from 2008–2013 are used to initialize the simulation. Recruitment from brood year *y*, population *p*, and simulation s, $\hat{R}_{y,p,s}$, is predicted based on the spawning abundance and the estimated regime-specific spawner-recruit relationships. The number of returning age *a* fish in calendar year *t*, for each population *p*, in each simulation *s* is given by

$$A_{t,p,s,a} = \hat{R}_{y,p,s}\, p_{p,a} \qquad (1.2)$$

where $p_{p,a}$ is the average age of return for the stock (see Table A.1). Spawners for year *y* are then

$$S_{y=t,p,s} = \sum_{a \in \{1.2,1.3,2.2,2.3\}} A_{t,p,s,a} - C_{t,p,s} \qquad (1.3)$$

the number of returning adults minus the estimated catch, $C_{t,p,s}$, from the management and production models discussed below.

Management Model

Managers in Bristol Bay face several challenges in achieving their escapement targets each season. To balance harvest across early- and late-returning subpopulations, managers attempt to spread harvest across the season to impose equal harvest rates on all stocks harvested within mixed-stock commercial fishing districts. However, actively managing commercial fishing effort relies on judgement of what cumulative escapements should be achieved through a given day-of-the-season. This is confounded by variation in both run size and arrival timing. Managers open and close individual districts, or river-specific “special harvest areas”, for fishing on a daily basis, but using lagged information about fish migrating from the commercial fishing district at the river mouth to upriver escapement enumeration sites. Further, river-mouth abundances, and catches, are a mixture of stocks from several component river systems especially on the east side.

The management model, described in Cunningham et al. (2015b), incorporates three key implementation uncertainties. For each year in the forward simulation, the management model first takes the annual run size by stock from the biological model and partitions them into daily stock-specific arrivals to each district. The arrival timing is randomly drawn from patterns observed during 1963–2008. The number of fish entering each fishing district in each simulated year *t* is

$$E_{t,p,s,d} = P_{t,p,s,d} \sum_{a \in \{1.2,1.3,2.2,2.3\}} A_{t,p,s,a} \qquad (1.4)$$

the product of $A_{t,p,s,a}$, the annual abundance of arriving sockeye by stock s, and $P_{t,p,s,d}$, the proportion of total annual return of population *p* arriving on day *d*.

The simulated managers select which fisheries to open on each day of the season by comparing observed cumulative escapement for each stock to the target cumulative escapement based on available information through that date. They know that the number of fish entering the fishing district, less the harvest on each of the preceding days of residency *r*, equals the number of fish leaving the district on day *d*:

$$L_{t,p,s,d} = \sum_{r=1}^{2} (E_{t,p,s,d-r} - H_{t,p,s,d-r}) \qquad (1.5)$$

The number of fish leaving the district is adjusted by the number of days it takes to get from the fishing district to the counting site, providing lagged information to the simulated manager in deciding whether to open the district or not. If the cumulative escapement on day d exceeds the expected escapement through that day necessary to meet the escapement target, given the average arrival distribution for that stock, the fishery is opened. If the cumulative escapement on a given day any stock harvested within a mixed-stock fishery is below the target level, the fishery is closed the subsequent day.

When the manager opens a fishery, f, daily harvest is given by

$$H_{t,p,s,d} = E_{t,p,s,d}\, h_{f,p} \qquad (1.6)$$

where $h_{f,p}$ is the stock-specific harvest rate in each possible spatial fishery opening, f. This parameter takes into account interception rates for each commercial fishing district, section, and special harvest area (Table A.2 and Table A.3), and is tuned through an iterative process of comparing management model predicted escapement outcomes to observed escapements for years 1963–2008. Importantly, this harvest rate is independent of the number of vessels in the district: regressing total daily harvest on active vessels and reconstructed district-specific abundances reveals that the ability to harvest the available fish is independent of fishing effort. Because harvesters participate in a derby with as much as five times the required capacity (Link et al. 2003), the data suggest there is always enough capacity to harvest all biologically available fish.

Processor Product Form Choice

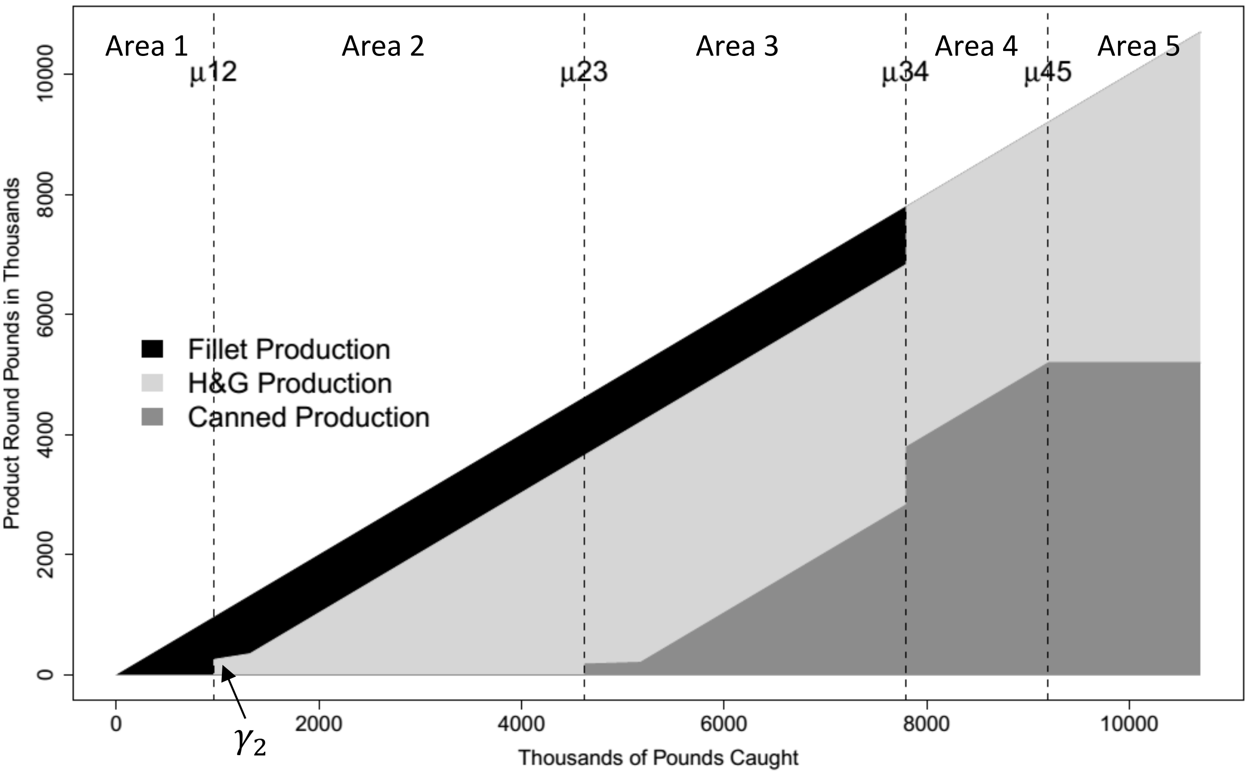
The daily harvests from the management model affect processors' choice of which products to produce, constrained by the processors' pre-season choice of how much labor to transport to the region, and the long-run decisions regarding processing capacity. We first describe the model of daily product form choice, and then capture how processors back out their seasonal labor and plant capacity choices.

Daily Product Form Choice

Cans, headed & gutted frozen fish (H&G) and frozen fillets represent 95% of the product value from Bristol Bay (Knapp et al. 2013). The choice of product form is driven by total landings each day: the fixed labor pool can direct more fish to minimally processed canned and H&G products than into higher-priced, more intensively handled fillets. Thus, predicting economic effects requires predicting these daily product form decisions, which are a function of physical capital, and the quantity of labor which is brought into the Bay in any season, based on the preseason run size forecast. However, developing a daily decision model is complicated by the fact that product form data is reported for only total annual production. We therefore build a daily bay-wide product form model based on factors that interviewed processors indicated were important, calibrate it to match observed production quantities in recent years, and validate our calibration with processing representatives on our advisory panel.

We model processors' daily production decisions with a series of threshold points in daily bay-wide landings. Based on COAR report production data and advice from processing experts, we model a Baywide total of 8 fillet, 16 H&G and 26 canning lines. The daily processing capacity of a standard fillet, H&G, and canning line is 120, 250, and 200 thousand pounds of whole fish (55, 114, and 91 thousand kg), respectively. In addition, at peak season, processors often have the capacity to ship a total of 1.5 million pounds (682 thousand kg) of whole fish per day to plants outside the Bay (all H&G) using contracted "haul-out" vessels. Whole fish average six pounds (2.73 kg). Fillet, H&G and canned products yield 0.5, 0.72, and 0.65 of the whole fish weight, based on estimates from Alaska Office of Fisheries Development (DCCED). Running all fillet, H&G and canning lines at full capacity requires 26%, 42.5%, and 57.5% of the current maximum labor force, respectively, and based on processor interviews, pre-season staffing does not exceed that needed to run all canning and H&G lines concurrently, leading to a baseline maximum staffing of $N_{\max}$=3390.

The model is calibrated using the daily landings and annual aggregate product mix from 2008, when fillet lines became prevalent, to 2013. We divide the range of possible daily catch values into five different product mix regions, denoting thresholds between regions as $\mu_{12}, \mu_{23}, \mu_{34}, \mu_{45}$ (Figure 1.2). Intuitively, processors produce the most profitable and labor-intensive product, fillets, when daily catch is low (less than μ_{12}). When daily catch exceeds the daily production capacity of the filleting lines, some labor is diverted to H&G (between μ_{12} and μ_{23}). Since the fish caught are split between H&G and fillet, we estimate the proportion of fish processed into fillets, γ_2, which is constrained by the fillet line capacity. As daily landings increase further, processors direct resources to canning lines, producing a mixture of all three products (between $\mu_{23}$and μ_{34}). Assuming processors produce fillets at maximum capacity in this region, we estimate the proportion of the remaining fish that is canned, γ_3. When daily landings exceed the point where producing all three products is no longer feasible due to labor constraints (between μ_{34} and μ_{45}), they pull labor from fillets and we estimate the proportion of canned products, γ_4, which is constrained by both the H&G and canning production capacity. Finally, when daily landings exceed μ_{45}, canning capacity is fully utilized, and additional fish is tendered to H&G plants outsize Bristol Bay.



At low daily landings (Area 1), plants produce labor intensive, high margin fillets. As landings increase beyond μ_{12}*, they add labor and introduce H&G production, and at* μ_{23}*, add lower margin canning production. At* μ_{34}*, the fixed labor supply labor is reallocated from filleting to canning, and beyond* μ_{45} *all capacity within the bay is exhausted and processors use tender vessels to ship fish to H&G plants outside the region.*

Figure 1.2. The modeled relationship between daily catch volume and processed product mix

Since μ_{12} is determined by the total fillet production capacity across processors (960 thousand pounds (436 thousand kg) of whole fish per day), and the joint production capacity limit of canning and H&G determine μ_{45} (9200 thousand pounds (4182 thousand kg) of whole fish), we only need to calibrate $\mu_{23}\ and\ \mu_{34}$, in addition to the slope parameters. Using observed daily landings from 2008-2013 as inputs, five parameters are calibrated such that the sum of absolute differences between observed annual production and predicted annual production by product form, is minimized with $\gamma_2, \gamma_3, \gamma_4$ equal to 0.73, 0.05, and 0.39 and μ_{23}, μ_{34} equal to 4622 thousand and 7796 thousand pounds (2101 thousand and 3544 thousand kg) respectively (Table 1.3).

Table 1.3 Calibrated Parameters for Relationship between Daily Volume and Product Mix

Slope of fillet in area 2 (γ_2)	0.73	μ_{12}	960,000 lbs whole fish	436,000 kg whole fish
Slope of canned in area 3 (γ_3)	0.05	μ_{23}	4622 thousand whole pounds	2101 thousand whole kilogram
Slope of canned in area 4 (γ_4)	0.39	μ_{34}	7796 thousand whole pounds	3544 thousand whole kilogram
		μ_{45}	9200 thousand whole pounds	4182 thousand whole kilogram

Long-run Plant Scaling

While the product mix thresholds in the daily model reflect recently observed levels in bay-wide capitalization, if changing biological management led to consistently larger run sizes, any associated changes in harvests would be expected to stimulate investments (or disinvestments) in processing capacity relative to current conditions. However, it is not optimal for processors to build plants so large as to be able to process the maximum possible run size; as evidenced by plants putting their fishermen on daily landings "limits" for two or more peak-run days in about 40% of recent years.

Modeling possible processor responses to changes in future runs is difficult because the limited annual-level data is confounded by the emergence of aquacultured salmon products, which have transformed the market for wild salmon products (Knapp et al. 2007). Rather than building a statistical model that attempts to control for such confounding variables on few observations, we develop a calibration to predict future changes in processing capacity based on the days during an average season processing capacity constrains catch. Processors face strong incentives to limit the number of times they must put their fishing fleets on limits during any season. Maintaining a consistent ex-vessel market is important to attracting a fleet of productive highliners in future seasons, and processors wish to maintain market share of their wholesale products. Preseason forecasts and recent years' harvests are used by processors to gauge their short and long-term investments in capacity to minimize use of limits on their fleets within the coming season.

Since 2000, processors have averaged 2 days on limits per season, providing a revealed preference benchmark for striking a balance between processing enough fish to provide markets to harvesters, and to supply wholesale markets, and the cost of maintaining lines that may not get used in every season. To evaluate alternative capitalization strategies, we scale up the daily capacity and threshold values in Figure 1.2 by a factor δ of daily processing capacity in 2014, reflecting a percentage increase in the number of each type of processing line. This scaling applied across all products (i.e., fillet, H&G, and canned) such that thresholds μ_m where $m = 12, 23, 34, 45$ are modified to $\bar{\mu}_m = \mu_m(1+\delta)\ \forall\, m$ and $\overline{N}_{max} = (1+\delta)N_{max}$; slopes remain unchanged.

Preseason Staffing

Given a fixed plant size, processors can scale their costs to the anticipated run size at the seasonal level by controlling the quantity of labor hired. Due to the remote location of Bristol Bay, workers, like other processing inputs, have to be shipped into the region before the fishing season starts; they live in dormitories on site. Only 1.7% to 3.5% of processing employees are local residents. Since it is costly to fly in and house more workers than necessary or to have insufficient labor to process harvested fish, processors carefully consider how many workers to hire prior to the start of a season. We predict the number of workers hired in each year t, N_t, as a function of the preseason forecast in thousands of fish.

$$N_t = \beta_{11} + \beta_{12}\, PreseasonForecast_t + \epsilon_t \qquad (1.7)$$

Equation 1.7 is calibrated using annual observations from 2001–2012 from the Alaska Department of Labor and Workforce Development, and the University of Washington Forecast Reports for Bristol Bay salmon. We use $\beta_{11} = 1209$ and $\beta_{12} = 0.074$, suggesting a forecast of an extra million fish leads processors to bring an additional 74 workers.[1]

Pricing Model

Since the alternative escapement goals may alter the run sizes, and thus catch and product composition, it is necessary to determine the responsiveness of global-market wholesale prices for each product to changes in Bristol Bay production quantities. This is challenging because the data available for each product form are different, and in some cases, limited. We consider the wholesale markets for canned salmon and filleted and H&G salmon separately (Asche et al. 1998; Knapp 2004).

We model price responsiveness with a single price equation, rather than a supply-demand system. Since prices are observed annually, there is little data (fewer than ten observations in some cases) to support a model with more parameters. Further, quantity is exogenous because product form is determined during the season based on daily landings, and prices for most wholesale transactions are not negotiated until after the season closes and processors know what they can and must sell.

Wholesale Price of Canned Sockeye

Knapp (2004) argues that the wholesale price of canned sockeye is driven by the available supply in the current season. We use data from the 1980–2010 National Marine Fishery Service (NFMS) annual export data set and annual COAR reports (NFMS and ADF&G COAR). To control

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[1] This model isolates the demand for labor. Since workers' actual pay depends on the number of hours worked, which is unknown to workers before the season, wages received do not influence the labor hiring decision in this case. Alternatively, unemployment rates for the USA/Alaska region could proxy for labor supply decisions. However, the processing industry used foreign workers (via J-1 visa) until 2012, making this approach to endogeneity infeasible.

for demand effects on the wholesale prices in Bristol Bay, we first estimate export price of canned sockeye as a function of exported canned sockeye quantities (ECQ_t); export price of canned pink salmon ($ECPP_t$); and Bristol Bay canned production ($BBCQ_t$).

$$\ln(ECP_t) = \beta_{21} + \beta_{22}\ln(ECQ_t) + \beta_{23}\ln(ECPP_t) + \beta_{24}\ln(BBCQ_t) + \nu_t \qquad (1.8)$$

It is necessary to include pink salmon in this relationship as past price-quantity relationships are influenced by the prices of substitute products, and omitting this relationship would lead to biased estimates of price responsiveness (Johnson and Wood 1994). Then we use the predicted value for ECP_t to estimate:

$$\ln(BBCP_t) = \beta_{31} + \beta_{32}\ln(BBCQ_t) + \beta_{33}\ln(ECP_t) + \epsilon_t \qquad (1.9)$$

where *log* wholesale Bristol Bay canned price ($BBCP_t$) is modeled as a function of *log* Bristol Bay canned sockeye production ($BBCQ_t$) and predicted *log* export price of canned sockeye (ECP_t). The first stage regression controls factors that may influence the demand for Bristol Bay canned sockeye; this isolates the own-product quantity effect on price, which lets us predict how prices will change with quantity at average price levels of substitutes. The second stage regression takes the predictive first stage results to estimate how Bristol Bay prices respond to the quantity produced. This process allows us to correct for any inconsistencies that may arise from estimating inverse supply and inverse demand equations simultaneously. Given the small sample sizes, we report nominal estimates as calibration values for use in the forward simulation, rather than as complete econometric demand models, though goodness-of-fit and standard errors are reported in Table 1.4. With the data in 1982 dollars, the calibration values for $\beta_{21}, \beta_{22}, \beta_{23}, \beta_{24}$ are 3.61, -0.25, 0.52, and 0.02, and the values for $\beta_{31}, \beta_{32}, \beta_{33}$ are 0.38, -0.17, and 1.04 respectively (Table 1.4). This suggests that Bristol Bay canned sockeye prices fall 0.17% with a 1% increase in production.

Table 1.4 Coefficient estimates and summary statistics for model equations

Equation	β_{n1}	β_{n2}	β_{n3}	β_{n4}	Observations	R^2
1.7	1209.41 (802.72)	0.0738* (0.0237)			12	0.4936
1.8	3.6140** (1.1048)	-0.2503* (0.1142)	0.5186** (0.0878)	0.0183 (0.0649)	21	0.8795
1.9	0.3811 (1.009)	-0.1747* (0.0843)	1.0412** (0.1516)		21	0.8094
1.10	3.4625** (1.1732)	-0.2183** (0.0688)	0.9867** (0.1444)		13	0.7876
1.11	1.0103** (0.3091)	-0.0431 (0.0240)	0.9279** (0.1809)		13	0.7602
1.12	0.0782 (0.1136)	0.8224** (0.1398)			11	0.7936
1.13	5.0794** (0.5703)	0.7254** (0.0379)			11	0.9760
1.14	-1.258e+07** (1.917e+06)	0.5449** (0.0524)	0.6886** (0.0410)	0.3026** (0.0781)	10	0.9983

Standard errors in parentheses, ** $p<0.01$, * $p<0.05$

Wholesale Prices of Filleted and H&G Sockeye

While the demand for frozen sockeye products has been studied extensively (Asche 1997; Asche and Wessels 2002; Williams et al. 2009), that work has not treated H&G and fillets as separate products. This is likely because filleting only became common in Bristol Bay in the early 2000s, so there are only a limited number of annual observations. NMFS trade data do not distinguish fillets and H&G products, so we use the 2001–2013 data on prices and quantities from the Alaska Department of Tax Revenue, and NMFS annual import prices (ATR and NMFS).

The annual average wholesale price of Bristol Bay H&G ($BBHGP_t$) and Alaska fillet (AFP_t) are predicted by estimating equations 1.11 and 1.12 simultaneously, where we use Bristol Bay annual H&G production ($BBHGQ_t$) and import price of frozen farmed Atlantic salmon fillet

(IP_t) as two predictors for Bristol Bay H&G wholesale prices and Alaska fillet production (AFQ_t) and IP_t as explanatory variables for Alaska fillet wholesale prices.[2]

$$\ln(BBHGP_t) = \beta_{41} + \beta_{42}\ln(BBHGQ_t) + \beta_{43}\ln(IP_t) + \epsilon_t \qquad (1.10)$$

$$\ln(AFP_t) = \beta_{51} + \beta_{52}\ln(AFQ_t) + \beta_{53}\ln(IP_t) + \nu_t \qquad (1.11)$$

This technique, seemingly unrelated regression, is adopted because we believe that two equations are related through correlation in the error terms. Frozen farmed Atlantic salmon fillet is treated as the primary substitute for frozen wild Pacific sockeye products (cf. Williams et al. 2009; Asche et al. 1998). The estimates for $\beta_{41}, \beta_{42}, \beta_{43}$ are 3.46, -0.22, 0.98 and the estimates for $\beta_{51}, \beta_{52}, \beta_{53}$are 1.01, -0.04, and 0.93 respectively (Table 1.4). This suggests prices fall 0.22% for a one percent increase in Bristol Bay H&G production.

To predict the wholesale price for Bristol Bay fillets specifically, we need to establish the relationship between Alaska and Bristol Bay wholesale price and quantities:

$$\ln(BBFP_t) = \beta_{61} + \beta_{62}\ln(AFP_t) + \epsilon_t \qquad (1.12)$$

$$\ln(AFQ_t) = \beta_{71} + \beta_{72}\ln(BBFQ_t) + \epsilon_t \qquad (1.13)$$

where the wholesale Bristol Bay fillet price ($BBFP_t$) and quantity ($BBFQ_t$) are linked as proportions of Alaska fillet quantity and price. We estimate the relationships using annual ATR data from 2001-2013. The estimates for $\beta_{61}, \beta_{62}, \beta_{71}, \beta_{72}$ are 0.08, 0.82, 5.08, and 0.73 respectively (Table 1.4). Combining equations, Bristol Bay fillet prices fall 0.02% with a one percent increase in Bristol Bay production, likely reflecting fillets produced in Bristol Bay are a small part of a market dominated by foreign-processed sockeye fillets and aquaculture.

Ex-vessel Prices

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[2] We use the wholesale Alaska fillet price rather than Bristol Bay for equation 1.11 because data from Bristol Bay alone is not available: since the number of processors is small, and the adoption of filleting slow, much of the time series does not have the three firms producing fillets in a year that is necessary for data to be non-confidential.

Because of different processing costs, different product compositions may lead to different shares of wholesale revenue going to harvesters as payments for fish. Knapp (2013) argues that the share of wholesale revenue that is passed to harvesters has been stable since the early 2000s.[3] We modify Knapp's model to capture any variation associated with product mix decisions, allowing for different (unobserved) profit margins by product form.

$$EP_t * (BBCQ_t + BBHQ_t + BBFQ_t) = \beta_{81} + \beta_{82}\, BBCP_t \times BBCQ_t + \beta_{83}\, BBHQ_t \times BBHP_t + \beta_{84}\, BBFQ_t \times BBFP_t + \epsilon_t \qquad (1.14)$$

We first estimate ex-vessel values (where EP_t is ex-vessel price) as a function of processor wholesale values by product form using annual ATR data from 2001–2013. To recover ex-vessel prices for the season, we divide the ex-vessel values by predicted aggregate processor production quantities from daily product form choice model. After covering fixed costs, we find harvesters are paid 54.5% of canned wholesale revenue, 68.9% of H&G revenue, and 30.3% of fillet revenue.

Forward Simulation

To evaluate impacts of the alternative escapement goal policies, we use the biological, management, and economic models to simulate the future, from a starting point of recent stock-specific escapements and current global market conditions. Reported results for these "forward simulations" average over 1,000 iterations describing uncertainty in future production dynamics, for the period 2014-2113 for each of the three different escapement goal policies.

An iteration of the simulation starts with determining the total number of fish returning for each stock, based on previous years' escapements through the biological model. We then generate

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[3] Williams et al. (2009) applied simultaneous equation equilibrium model of supply and demand to Alaska's ex-vessel sockeye prices and revenues. They modelled statewide ex-vessel price as a function of real prices for Alaska sockeye salmon exported to Japan and other places, and the lagged ratio of Alaskan real ex-vessel price of sockeye salmon to the real export price of Alaska sockeye salmon exported to Japan. Since our focus is on how changes in product mix arising from the profile of daily harvests within Bristol Bay affects ex-vessel prices, we build on Knapp's (2013) approach.

a preseason forecast observed by processors, based on the actual run size and a log-normally distributed observation error calibrated to the scale of recent preseason forecast errors:

$$PreseasonForecast_t = Actual\ run\ size_t * \eta_t$$

$$\eta_t \sim logNorm(0.0204, 0.2184) \qquad (1.15)$$

From this, we use equation 1.7 to generate the number of workers brought into the Bay for the coming season. The predicted number of workers hired in year t, $\widehat{N_t}$, is truncated at $\bar{N}_{max}$ and used to scale product thresholds points μ_m, where $m = 12, 23, 34, 45,$ such that $\hat{\mu}_{mt} = \frac{\hat{N}_t}{\bar{N}_{max}}\bar{\mu}_m$.

The timing and duration of the run is matched to a random historic observation. Daily catch and escapement, based on simulated management performance, are generated for the annual return. In order to operationalize the daily production model, we add two intertemporal considerations that processors emphasized play a role in their daily decision-making. First, we calculate a three-day moving average process of the daily catch from the management model. This reflects processors' ability to carry-over some landings from one day to the next. Second, we capture a small, inelastic demand market for canned salmon by ensuring a minimal quantity is produced. We establish a behavioral rule of thumb that if canned production is lower than 5.65 million pounds (2.57 million kg) of whole fish, the minimum observed in the period 1984-2010, by July 11th, all the fish that are caught after that date will be canned until 5.65 million pounds of whole fish are processed into cans. The chosen date ensures this product switch happens only after the peak of the season, when it would not happen based on daily landings.

Next, we capture events where daily catch exceeds processing capacity. Even though we smooth daily catches with a three-day moving average, we still observe situations where the smoothed daily catch exceeds daily processing capacity. In the field, the processors put harvesters on daily landings limits. We represent the biological implications of daily harvester limits by allowing the amount of fish exceeding the processing capacity to become additional escapement, which influences future returns through the recruitment simulation model. This feature incorporates economic decisions as a driver of biological outcomes within our integrated MSE model.

Given daily catch from the MSE framework and the number of workers predicted from preseason staffing decision model, the within season-processor model predicts daily production of fillets, H&G, and cans using the parameter values presented in Table 1.3. Given annual aggregate production of each product, we calculate wholesale and ex-vessel prices using equations 1.8 to 1.14, with parameter values reported in Table 1.4. The forecasts adopt the most recent 5-year average export price of canned sockeye, \$5.81 per pound (\$12.78 per kg), and import price of frozen Atlantic salmon fillets, \$1.94, as constant in the forward simulations. To ensure that harvesters do not end up receiving negative payments, we stipulate that processors pay harvesters a minimum of 10 cents per pound (22 cents per kg) of whole fish. We then convert values to 2013 dollars (inflating by 2.44), completing an iteration of the forward simulation. This is repeated 1000 times to evaluate each escapement goal scenario, given uncertainty in the biological and management processes.

Long-run Plant Scale Calibration

The remaining calibration is to determine the level of long-term capital investment that meets the two-days-on-limits rule-of-thumb. We run the above model at δ equal to 0%, 15%, 20%, 25%, 35%, and 40%, and drop 2015-2040, a biological transition period, to capture a steady state result. A 20% increase (for current SEGs), a 25% increase (for proposed SEGs), and 35% increase (for BEGs) in processing capacity best fit the selection criterion described above (Table 1.5). Predicting a 20% increase in capacity under current policy corroborates our model, as at the time of the study a new plant for Silver Bay Seafoods was under construction, increasing bay-wide processing capacity by more than 15%. When we calculate average number of days-on-limits for a season across 100 simulations, we did not count years where daily processing capacity is exceeded due to insufficient labor, because that is not a long-run capitalization problem.

Table 1.5 Average number of days-on-limits at a range of increases in daily processing capacity

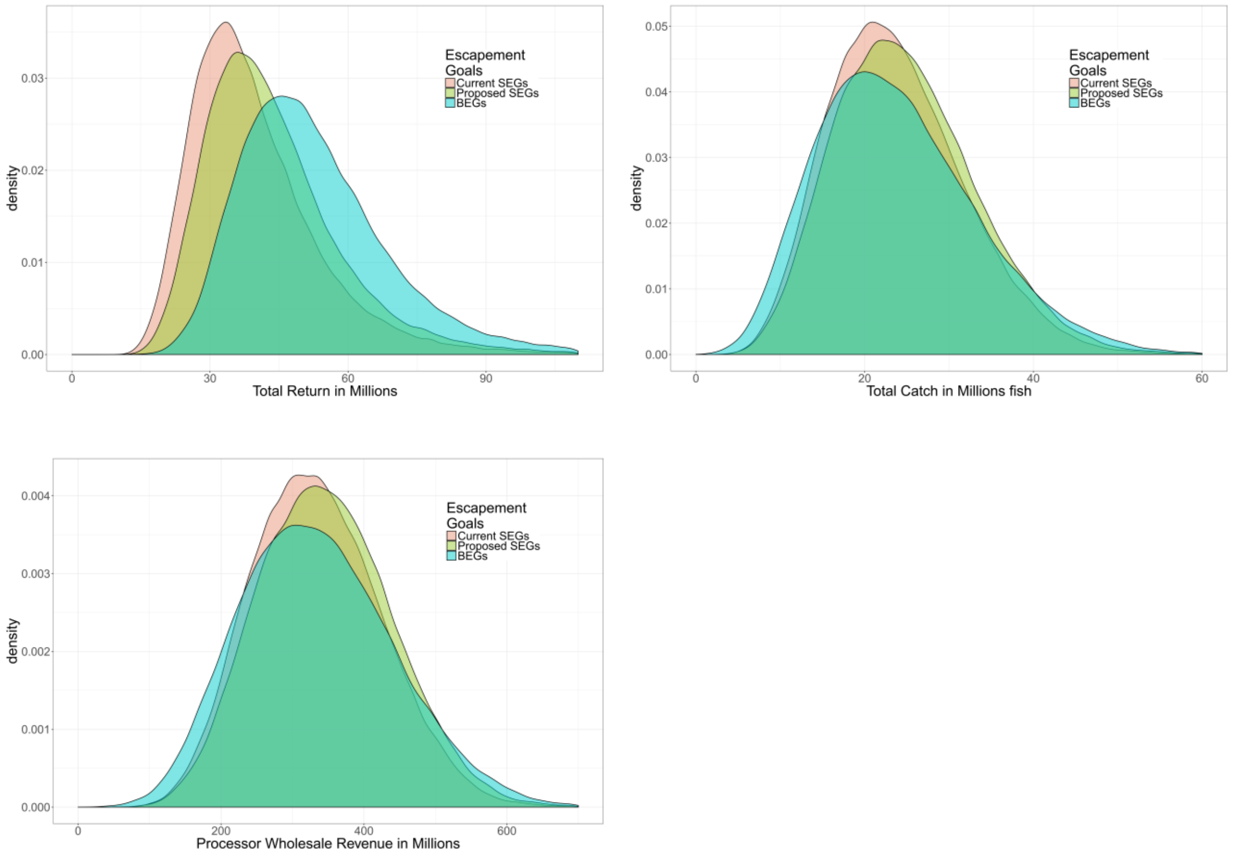
% increase in daily processing capacity limit	Current SEGs	Proposed SEGs	BEGs
No increase	3.76	4.35	4.34
15%	2.20	2.71	3.18
20%	1.90	2.31	2.85
25%	1.55	1.97	2.55
35%	1.09	1.42	2.03
40%	0.91	1.21	1.81

* These were averages from 1,000 simulations of 100 years each; we used the final 74 years of each 100-year simulation to compute the average.

To compare the alternative escapement goal scenarios, we examine the distributions of catch, and wholesale and ex-vessel revenues in steady state, excluding transitional years 2015-2040. We do not attempt to forecast decadal or century-scale trends in global seafood markets, but rather compare the alternative escapement goal policies under current conditions.

1.3 RESULTS

The model predicts that higher escapement goals are expected to lead to higher average run sizes across rivers. However, the inter-annual variation of the run size also increases, as shown in Figure 1.3a and the top section of Table 1.6. Much of the increase in mean is driven by a long right tail of infrequent but very large runs, a structure that has important implications for processors and harvesters. The right-skewed distribution of run size is driven by lognormally-distributed process variation in recruitment, and reflects the high level of variation in production observed for most stocks in the past. The BEG policy has the highest mean and highest inter-annual variance, followed by the proposed SEGs, and finally the current SEGs. Comparing the size of the changes from each scenario reveals a trade-off between the mean and variance of the run size.



* Thin right tails of the density graphs have been truncated.

Figure 1.3. Distributions of run size, catch, and wholesale revenues

Table 1.6 Summary statistics from forward simulations

	Current SEGs	***Proposed SEGs***	***BEGs***
Annual Return (all units in millions of fish)			
Median	36.93	41.03	50.25
Mean	40.43	44.49	54.17
Inter-annual variance*	413.74	489.95	681.13
Annual catch (all units in millions of fish)			
Median	23.00	24.18	22.85
Mean	23.81	24.93	23.94
Inter-annual variance*	54.99	61.70	79.99
Processor wholesale revenues (all units in millions 2013 dollar)			
Median	329.37	343.14	328.48
Mean	334.19	347.23	335.41
Inter-annual variance*	6,957.09	7,689.94	10,079.54
Vessel revenues (all units in millions 2013 dollars)			
Median	155.08	162.93	153.30
Mean	158.60	165.83	158.04
Inter-annual variance*	2,459.20	2,721.27	3,582.63

Percent change between current SEGs and other escapement policies	***Proposed SEGs***	***BEGs***
Annual Return (all units in millions of fish)		
% change in Median	9.71	33.88
% change in Mean	10.86	37.87
% change in Inter-annual variance*	23.73	108.28
Annual catch (all units in millions of fish)		
% change in Median	4.77	0.23
% change in Mean	5.13	1.47
% change in Inter-annual variance*	13.56	49.98
Processor wholesale revenues (all units in millions 2013 dollar)		
% change in Median	3.92	0.54
% change in Mean	4.16	0.92
% change in Inter-annual variance*	11.42	48.31
Vessel revenues (all units in millions 2013 dollars)		
% change in Median	4.67	-0.20
% change in Mean	5.11	0.54
% change in Inter-annual variance*	11.64	49.60

*The Inter-annual variance is based the mean of inter-annual variance within each iteration, averaged across iterations.

While average run sizes are higher under the proposed SEG and BEG policies, they do not translate into higher catches or processor revenues. Figure 1.3b, Figure 1.3c and the second and third sections of Table 1.6 both suggest similar average catches and processor revenues compared to the status quo SEG policy. For the (high escapement) BEG scenario, we predict a 1.33% decrease in the median catch, the same mean, and a 48.8% increase in inter-annual catch variation. While BEGs represent MSY in Fair et al's (2012) model,[4] they do not increase average harvests and do increase variability in our simulation. Two competing pressures of higher escapement goals explain this divergence between run size and catches. First, higher escapement goals require that more returning fish be preserved for escapement, rather than catch, so in low-run years, catches are lower. Second, the more frequent high-run years are not frequent enough to support investment in the capacity to process all the additional fish available for catch. The value of this fish is thus eroded because processors make less valuable (canned) products, or put harvesters on limits during the peak of the run in abundant years, allowing it to escape. Compared with the BEGs, the proposed SEGs make a marginal change in the escapement goals that better balance years of limited fishing and exploitability of larger runs, leading to an increase in total catch and processor revenue of about 1% above the status quo SEGs.

These Bay-wide results aggregate across outcomes for individual fishing districts, but district level outcomes are important because not all fishermen can move among districts. Since different river systems have different run variabilities, some may experience more frequent years with few or no openings in order to meet higher escapement goals, leading to imbalanced or unacceptable distributional impacts among different components of the harvesting sector. To analyze district-specific effects, we show the number of days each east side commercial fishing

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[4] Note that our state-transition model implies different MSY escapements than Fair et al.'s (2012) single regime model.

district is open to fishing between June 20 to July 17 of each simulated year, the time frame in which most of fishing activity occurs. The east side stocks include Kvichak, Alagnak, Naknek, Egegik, and Ugashik. (See Figure A.1 for other stocks.)

Figure 1.4 shows the cumulative distribution of the number of simulated years across which a given district is open to fishing for the number of days on the X-axis in the steady-state period of our forward simulations, averaging across iterations. The current SEG policy, furthest to the right, provides the most fishing opportunity in all districts. The slightly higher escapement goals of the proposed SEGs follow a similar pattern, whereas the BEG scenario is well to the left of the other two scenarios. This reflects that the individual districts are likely to have fewer fishing opportunities under BEG management, relative to the other two scenarios. For example, Ugashik is predicted to have zero fishing openings once in every five seasons, whereas under the other two escapement goal policies, Ugashik is completely closed only once every 20 years. Similarly, Egegik will offer no fishing opportunities once every 6-7 years under BEGs, but will offer at least some fishing 199 out of 200 years under either current or proposed SEGs. The rates of closure under the current and proposed SEGs are similar because openings are influenced not only by these stocks, but also other (more abundant) east side stocks that swim through these districts. These closure rates are consistent with a recent 20-year period (1995-2015) when the annual returns were less than the lower range of the BEG twice in Ugashik and once in Egegik.

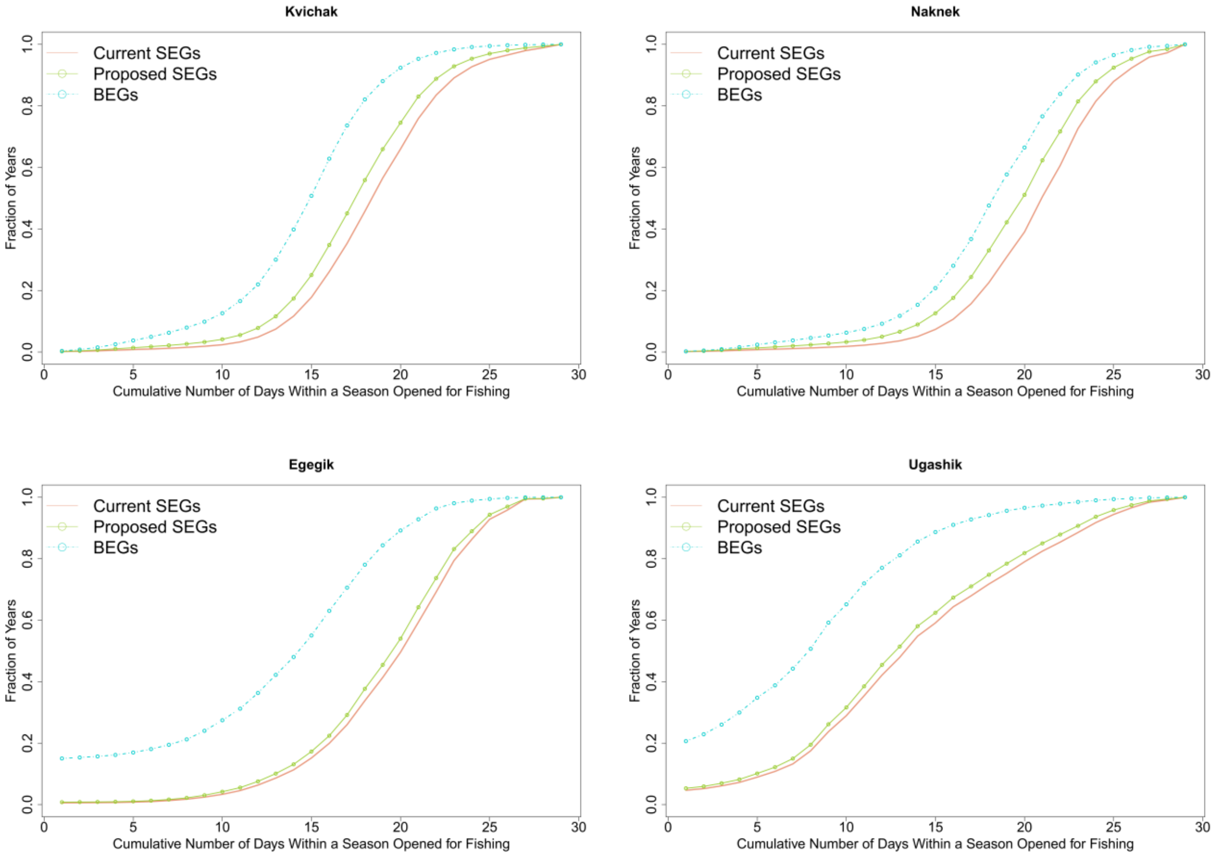

Figure 1.4. Cumulative densities of number of days each district is open to fishing between June 20th and July 17th

However, fewer opening days per season may not translate into lower ex-vessel revenues, if daily catches are larger. Figure 1.5 shows the distribution of ex-vessel revenue estimates for the Naknek-Kvichak, Egegik, and Ugashik districts.[5] For the Egegik and Ugashik districts, BEGs lead to lower average ex-vessel revenues, and a considerably higher chance of years with zero revenue, than the other two scenarios, which are comparable in all districts (see also Figure A.2).

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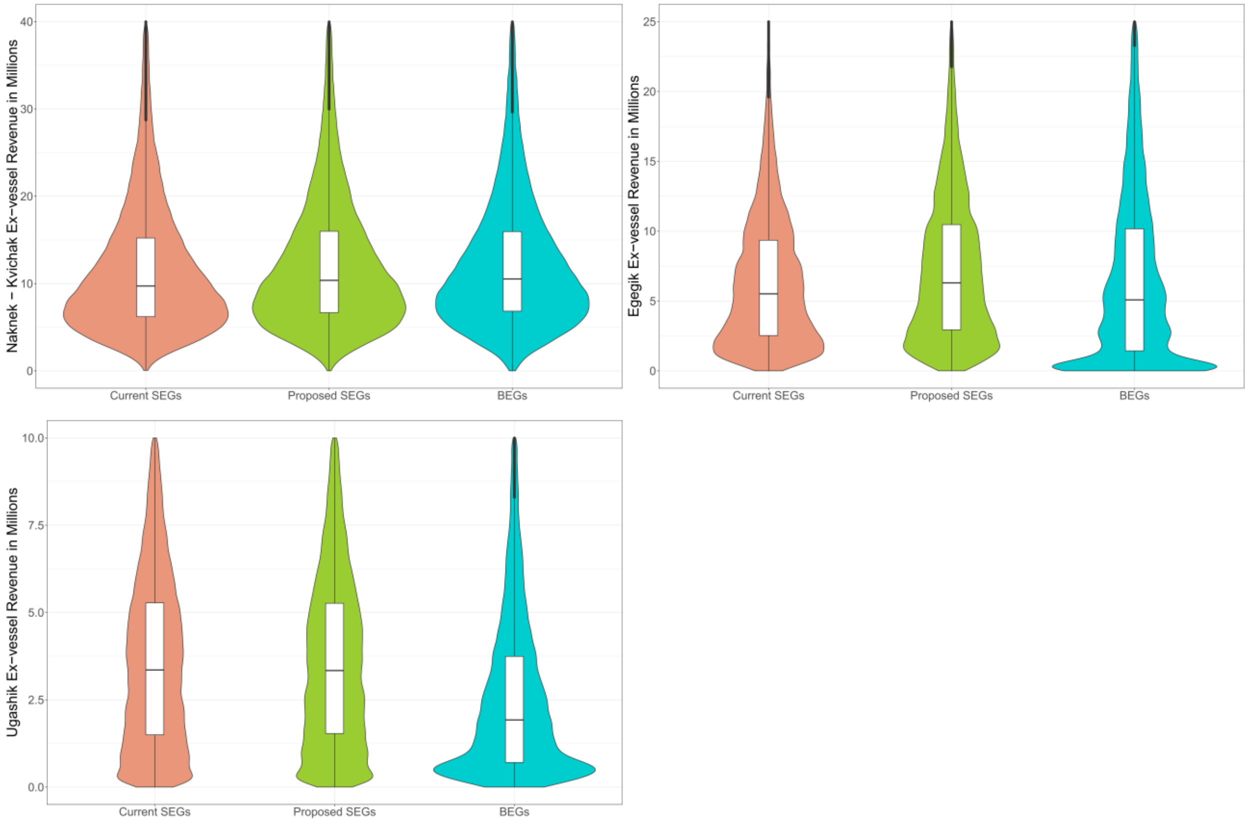
[5] The daily catch results were constructed using harvest rate by stock, rather than harvest rate by district. The stock-based structure of the biological model makes it infeasible to precisely establish ex-vessel revenues for the east side districts due to cross-stock catch. For example, when the Ugashik district is opened, catch is comprised of not only the Ugashik stock, but also Naknek, Kvichak, and Egegik fish on their way through Ugashik district on their way to their spawning rivers. These graphs are meant to be illustrative of the distributional considerations associated with limited openings in individual systems.

Both district closure frequencies and district-specific ex-vessel revenues suggest that even if higher escapement goals would lead to higher mean annual catch, the set-net sector and less mobile vessels may not necessarily benefit. Although the number of days open in each district decreases when the escapement goals are raised, the Bay-wide total annual catches still increase. This implies that the independent stochasticity (variability) in returns across different river systems insulates mobile harvesters against closures in any particular district. Even if one district is closed for fishing due to lack of returns for the season, other districts can experience higher average returns supported by higher escapement goals, so the total catch can still be higher.



Violin density plots of ex-vessel revenues. The horizontal black line indicates the median value, and the white bos the inner quartile range.

Figure 1.5. Distributions of ex-vessel revenues

The decrease in district-specific openings under some escapement goal policies may also increase the proportion of years where little or no harvest opportunities are provided. We examine the probability of having total Bay-wide catch of less than 5, 10 and 15 million fish under each scenario (Table 1.7). Based on our simulation results, low harvests are more likely to occur under BEGs than the other two scenarios. Catches below 10 million fish occur once in every 23 years under BEGs, but only once every 60 years under either proposed or current SEGs. In addition, harvests below 15 million fish occurred 18.1% of the time under BEG management, almost twice as often as under the other policy scenarios. Between the two SEG policies, the current SEG yields a slightly higher probability of low-harvest seasons than the proposed SEG. This is consistent with our earlier results in which the current SEG yields slightly lower average catch than the proposed SEG. This also suggests that a slight increase in inter-annual variance under the proposed SEG relative to the current SEG does not seem to impact overall catchability.

Table 1.7 Percent of years when catches were less than 5, 10, and 15 million fish, Bay wide, across three escapement goal policies

Probability of catching less than:	**Current BEGs**	**Proposed BEGs**	**BEGs**
5 Million Fish	0.02%	0.03%	0.31%
10 Million Fish	1.94%	1.68%	4.43%
15 Million Fish	12.97%	10.76%	17.65%

1.4 DISCUSSION

We develop an economically sophisticated management strategy evaluation model, incorporating processing decisions and product pricing into an assessment of steady-state outcomes under three escapement goal policies: the current SEGs, proposed SEGs, and the BEGs based on Fair et al.'s (2012) estimate of MSY. We find that incorporating processor and market response shifts the nature of the advice given to managers (ADF&G) and the Alaska Board of

Fisheries, as more fish does not result in more money. Although average annual returns are considerably higher under the biologically motivated BEGs, average annual catches and processor wholesale revenues are comparable, and inter-annual variation is much higher.

This result illustrates one fallacy in the notion that fishery management policies that achieve MSY also support better economic and social outcomes for the fishery. Higher average fish returns under BEGs, relative to the other two scenarios, does increase (maximize) average potential sustainable yield, but behavioral responses to the associated variance mean that little of that potential yield is realized. In fact, our analysis predicts the MSY-based BEGs yield the lowest annual catch, despite BEGs' intended purpose. While daily landings can overwhelm daily markets or processing capacity leading to severe prices drops (e.g., Scheld et al. 2012), in those cases value was increased by adopting management that incentivized smaller daily landings over a longer period. Our model shows that run variability, compressed natural season length, and limited processing capacity interact to create a situation—the only one of which we are aware—where economic benefits are increased by reducing biomass below B_{MSY}.

The mean-variance tradeoff in Bristol Bay led Steiner et al. (2011) to suggest a constant harvest strategy, an idea whose most appealing feature is ignored in a typical MSY analysis (e.g., Bue et al. 2008): stable harvests are crucial to the stability of income to the harvesting and the processing sectors. This is particularly true for harvesters who specialize in one district in the Bay, as an increase in their district's escapement goal(s) would lead to higher district-specific closure rates. Even if the average Bay-wide catch is higher under higher escapement goals, including the proposed SEGs, the benefits will not be distributed equally across all harvesters. Set-net harvesters and less mobile driftnet harvesters might be worse off on average, and could be more vulnerable when their district experiences more frequent low catch, low-income years. Understanding this effect requires understanding human reactions to changes in fish abundance, here implemented with the daily management model and daily processing capacity.

To further extend the joint biological-economic sophistication of an MSE, additional economic approaches could be integrated. First, our steady state analysis is intended to facilitate long-run comparisons, but identifying the economically best policy would involve a cost-benefit analysis. This would calculate net present values, incorporating potential losses incurred during the transitional period as stocks build based on increased escapement goals, as well as the costs incurred due to any commensurate increases in processing capacity. Second, we generate future wholesale prices based on recent global market conditions, but these may change over time in foreseeable ways. For example, if continued competition from aquaculture puts pressure on wild sockeye prices, we may have further overestimated the potential value in increases in escapement goals and average run sizes. Incorporating a sensitivity analysis for pricing and processing technology parameters could indicate the robustness of our conclusions to possible future states of salmon markets.

To simulate the biological and management components of the Bristol Bay sockeye salmon commercial fishery we made several assumptions by necessity, which may be worthy of evaluating in subsequent research. In simulating the management process, we made two specific assumptions about the data streams used to guide daily fishing effort decisions. First, escapement of sockeye on to the spawning grounds was assumed to be observed without error. Escapement to each river system is enumerated using visual counts, occurring for 10 minutes on each bank of the river from an elevated tower during each hour of the day, or using bank-associated sonar in the case of the Nushagak River. Given the clear water in most rivers, high nighttime levels of ambient light at this latitude in the summer, and placement of counting towers, these escapement estimates are generally assumed to have low bias and high precision. However, that the observation error variance for escapement enumeration scales with the mean and may lead to greater implementation error during periods of high escapement. Second, the decision rules used to approximate in-season management behavior did not account for auxiliary information about salmon arrivals in addition to daily tower counts. These auxiliary data include aerial surveys of fish in the river between the fishing district and counting tower and daily catch per unit effort from the Port Moller Test Fishery which intercepts salmon during the homeward migration and is operated by the Bristol Bay Science and Research Institute (Flynn & Hilborn, 2004). While these auxiliary data streams may influence the in-season manager's decision process, it is unclear to what extent, and by necessity this information was not included. With respect to the simulation of Bristol Bay sockeye salmon biology, we assumed that both age and size at maturation were time-invariant, however there is some suggestion that weight-at-age is density dependent, having a negative correlation with return abundance, and that size at return exhibits an even-odd year pattern. While worth of further exploration, it is unlikely that ignoring these specific elements in our simulation of biological dynamics and the management process are unlikely to influence our overall results.

This case study also highlights important gaps in data that limit the nature and quality of economic outcomes that can be derived from the MSE model; this stands in stark contrast to the extensive biological data available in this fishery. Price and product form observations are limited to single annual values; data collection practices and confidentiality obscure plant-level variation that could provide insight into how product form and pricing decisions interact. Further, new products like fillets have very short time series, and most of the publicly available data sources do not distinguish the production of sockeye frozen fillets and H&G, limiting our ability to understand substitution between these on both the production or wholesale side. The processor model could also be better supported with annual surveys of number of days on limits, and Bay-wide processing capacity per line.

While this analysis focuses primarily on the behavioral response of the processing sector, economically sophisticated MSEs will broadly consider behavioral changes and distributional consequences arising from different management strategies. We did not explicitly incorporate harvest sector behavior because Olympic derby management has ensured sufficient harvest capacity was present in each day and each district, within the range of the data. During unusually abundant years, it is possible (though we think unlikely) that harvesting power is more limiting than the processing capabilities. However, future changes in management that affect participation, fleet capacity, or the ability to move among districts may affect outcomes. In particular, the MSE should consider who fishes? When? With what gear? Whether there will be environmental effects of that fishing behavior? And what effect will their behavior have on fishing costs? The latter are a key element of a complete welfare analysis.

In designing MSEs, analysts must identify and incorporate the primary sources of variation and uncertainty that might influence management procedures' attainment of objectives. Certain economic responses, such as inelastic market demand that lead to dramatic price decreases as quantity increases (this is uncommon), or highly costly behavioral changes that limit the fleet's exploitation of abundant stocks, are commonly considered ways that more fish may not lead to more money. This case study highlights the importance of considering behavioral responses to, and distributional consequences of, variability in abundance. Even with healthy stocks, harvesting and processing businesses are sensitive to variability in catches, and if variance is too high, they may fail to capture value from more abundant fish; indeed, they may be better off with a management strategy that provides for more consistent catches. Consistent catch management strategies will be favored in fisheries where daily processing capacity is exceeded in abundant years, or spikes in catch lead to the erosion of product value (cf. Homans and Wilen 2005). Further, even if total revenue increases under a management strategy, stabilizing catch may minimize downside risk, the risk of catches so low that some participants become vulnerable to bankruptcy, or are put in a position where they need to sell their fishing assets to deal with personal financial shocks. Thus, when fisheries are highly variable year-to-year, or there is significant heterogeneity in where in the structure of the resource stakeholders access it, understanding the consequences of alternative management plans indicates integrating models of the harvest and post-harvest sectors.

Chapter 2. MOBILITY RESTRICTION VERSUS HARVESTERS' EXPOSURE TO RUN VARIABILITY

Abstract

In an over-capitalized limited-entry fishery, a slightly less fishing capital in the water may not result in catching less fish overall. However, placing restrictions on mobility may expose harvesters to area specific run variability that could otherwise be avoided. Bristol Bay salmon fishery in Alaska, a prime example of such fishery, currently has a policy which penalizes vessels moving from one area to another with 48-hour of no fishing time in attempt to reduce short-term effort. To test the impact of mobility restrictions on harvesters, we examine three policies, 0-hour policy, 48-hour policy, and no switching policy, under simulation. We first estimate individual production function for each fishing district in Bristol Bay. Next, we predict individual catch and district movements under each policy in equilibrium. We find that the equilibrium predicted individual catches are on average highest under 0-hour policy, followed by 48-hour, with no switching policy catching the least. With introduction of run stochastic shocks to each fishing districts 100 times to study the relative degrees of exposure to run variability, the rankings of average harvester performance stay the same with gap and variances widen. The district-specialists and less powerful vessels are more susceptible to district-specific stochastic shocks. No switching policy subject harvesters to greater downside risks than other two policies.

2.1 INTRODUCTION

The traditional approach to commercial fishery management restricts inputs and imposes total catch limits (TAC) to manage for socio-economic objectives. While such approach is effective in managing for biological sustainability with TAC usually set at the maximin sustainable yield (MSY), it often leads to economic overfishing thereby failing the intended objectives (Munroe and Scott 1985). Any imperfect means of input control provides harvesters incentives to substitute inputs from regulated to unregulated and therefore increasing effort level gradually overtime (Wilen 1979). Such fisheries also provide incentives for harvesters to race against each other for a share of the catch before the total catch limit is reached by investing heavily on the unregulated inputs, reducing the net return to harvesters.

Bristol Bay salmon fishery, primarily for sockeye salmon (*Oncorhynchus nerka*), is a poster child of an over-capitalized limited entry fishery with biological success and economic failure (Hilborn 2006). There are two main methods of fishing in Bristol Bay, drift net and set net, with five commercial fishing districts, Togiak, Nushagak, Naknek-Kvichak, Egegik, and Ugashik districts (Figure 1.1). With high variability of run size from year to year and the characteristics of life cycle of salmon, escapement goals, the number of fish going up the river for spawning to ensure sustainable returns of fish in the future, are set for each fishing district for a season and fishery managers manage district openings and closures to meet the escapement goals. Since the implementation of the permit system back in 1975 transforming Bristol Bay from open-access to limited entry fishery, various of input controls, including the size of the vessel not exceeding 32 feet and the size of the net per vessel not exceeding 150 fathoms are also put in place.

Among all the input controls policies, Bristol Bay has a policy known as the 48-hour waiting period. The regulation states that if a harvester desires to go from one fishing district to another between June 25th to July 16th, harvesters must wait 48 hours before entering the new district. There are two objectives that this policy is designed to achieve: improve competitiveness of the set net fishery against the drift gillnet fishery and prevent harvesters simultaneously moving into a district with better than expected salmon run (Board of Fisheries 1986).[6] In particular, Board of Fisheries (BOF) supports the 48-hour policy with evidence found while temporarily reduced the waiting period to 24-hour in 1985. BOF sites the evidence that the set netter's catch share in Bristol Bay fell from a pre-1985 10-year average of 12% to 9% in 1985. With the historic return of fish in Ugashik and Egegik in 1985, the set net sector catch share fell from 11% to 3% for Ugashik and from 15% to 6% for Egegik. On the other hand, the set net sector catch share increased for those districts experiencing weak salmon run, with Naknek-Kvichak catch share increased from 10% to 12% and Nushagak from 17% to 30%. Another policy was put in place in 2004 in attempt to further reduce the effort level by allowing a vessel to fish with 200-fathom net if there are two permits onboard. Double-permit policy intends to reduce the number of vessels in the water without doubling the fishing effort per vessel.

Quantitatively, the 48-hour policy does have the benefit of displacing some capitals for a short period of time. Since harvesters incur two-day of no fishing time upon switching, switchers' vessels are temporarily displaced from water for two days. In a fishery that majority of fishing activity occurs during district registration period of 22 days, 2 days is a significant amount of time. With high penalty of switching, mobile driftnet harvesters are less likely to switch to a district experiencing a sudden influx of fish, leaving a bigger catch share of fish to set net sectors and homesteaders – drift net harvesters who traditionally fish and specialized only in one district. Homesteaders behaviors are similar to set net harvesters where they both are constrained to one district and do not change districts during the season.

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[6] Note that Togiak district is not subject to this rule because once a harvester has fished in the Togiak district, they are not allowed to fish in any other districts (and vice versa) until mid-August.

Qualitatively, 48-hour policy allows processors an easier time to coordinate tenders, which deliver fish from fishing ground to the processing plants.[7] It also potentially reduces fishing related injuries due to prolong fishing hours.[8] In addition, fishery managers, knowing ahead of time the number of harvesters that will be in a district, can manage district opening and closures easier to achieve escapement goals and maintain allocation of fish between drift and set net sectors.

Despite possible benefits, the 48-hour policy seems to be an arbitrary choice to control for short-term effort level and to provide set net harvesters and homesteaders a relief against mobile harvesters. A policy in which penalizes all switching behavior would seem to achieve intended objectives with more success. With no switching policy, however, shifts all the district-specific run variabilities to harvesters. When a district experiences lower than expected run, mobile harvesters have nowhere to go but stay and fight for a share of fish with homesteaders and set net harvesters under no switching policy. Not only are the mobile harvesters worse off since they are not able to switch other districts that could increase their catch, homesteaders and the set net harvesters now have a smaller share of fish to catch from due to competition from mobile harvesters who would have switched under policies with switching possibility. On the other hand, harvesters who are in a district experiencing higher than expected run are better off since they do not have to face new entrants from other districts.

This contrasts with a policy where harvesters can switch freely – a 0-hour policy. When a district is experiencing lower than expected run, a 0-hour policy on switching allows mobile harvesters to switch to other districts and alleviate some pressures for homesteaders and set net

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[7] We understand that one consideration of a harvester's district choice is tied directly to the processor that they sign up to deliver their fish to. This means that a harvester is unlikely to go to a district without a tender service offered by the processor. However, most processors in the bay do offer tender delivery services in the four main districts. In the case that a tender service is unavailable, the processor may have an agreement with other processors to ensure that their harvesters can deliver their fish to a tender offered by other processors.

[8] From personal interviews with harvesters, it is common for a harvester to go fishing for 72 hours without any rest during the peak of fishing season.

harvesters. When a district is experiencing higher than expected run, homesteaders and set net harvesters face more competitions from mobile harvesters.

Previous research has focused on the study of bay-wide run risks. Steiner et al. (2011) show that a constant harvesting strategy can minimize harvesters' exposure to bay-wide run risks. However, a constant harvesting strategy does not necessarily minimize harvesters' exposure to district-specific run risks. Anderson et al. (forthcoming) have also shown that homesteaders and set net harvesters are on average worse off when a policy increases the volatility of inter-season runs. However, whether intra-season volatilities also apply is the question.

If the main objective of the 48-hour policy is to improve economic welfare of harvesters, Link et. al (2003) have suggested a permit buy-back programs to reduce fishing effort level in Bristol Bay. However, economic theory has suggested that with a permit buy-back program, the effort level will only be reduced in the short-term. In the long-run, harvesters will slowly invest in unregulated inputs to bring the effort level back to pre-buyback permit period (Clark and Munroe 2002). Economic theories and real-world implementations of the individual catch share management have proven to effectively reduce effort level, race to fish, and improve economic profitability for harvesters (Grafton 1996). However, the Alaska state constitution prohibits such implementation and therefore outside the scope of this paper's discussion.

The restrictions on harvester mobility clearly have implications on harvesters' welfare. Whether or not harvesters, mobile or homesteaders, are better off or worse off as result of different policies, is not clear. Therefore, we set out to understand how mobility impact harvesters' exposure to district-specific risks under simulations. We first estimate production function for an individual vessel in Nushagak, Naknek-Kvichak, Egegik, and Ugashik districts from 2010 - 2012. We then simulate equilibrium individual catch for three policies, 0-hour, 48-hour, and no switching policy.

Lastly, we introduce a yearly district specific log-normal stochastic shock to the actual arrival of fish in each district one hundred times.

In the absence of stochastic shock, we find that our simulated aggregate daily predicted catch by district and year across three policies are similar to the actual catch, validating our simulation approach. Similar aggregate daily catch across three policies are also indicative of sufficient harvesting power in Bristol Bay. On the vessel level, average yearly equilibrium catch per vessel is the highest under 0-hour policy, hollowed by 48-hoir, with no switching policy catching the least. Higher mobility results in higher average catch in equilibrium. With introduction of yearly district specific run stochastic shocks, we find that harvesters on average perform the best under 0-hour policy, followed by 48-hour policy, with the worse performance under no switching policy. Stochastic shocks widen the gap and variance that we observe under non-stochastic shock scenario with the homesteaders and less power vessels are impacted the most. Downside risks, measured by the semi-variance of a harvester, the difference between predicted catch under stochastic and no stochastic shocks of all simulations, is the highest under no switching policy, followed by 48-hour, with the least under 0-hour policy.

The rest of the paper is organized as the following. We start with a section describing data sets that we use for this paper. It is then followed by the methodology section detailing steps for estimation and simulation process. Result and conclusion conclude the paper.

2.2 DATA DESCRIPTION

Out of three datasets we use in the analysis, the first data set is obtained from the Alaska Commercial Fisheries Entry Commission (CFEC), which contains Bristol Bay daily landings data by group and district from 2002 to 2012. Due to confidentiality reason, we are not able to obtain daily landings by individual vessel. Before receiving group level landings data from CFEC, we first group harvesters based on their vessel characteristics such as horsepower and refrigeration system and resident status—whether permit holders are from Bristol Bay Borough area, Alaska urban, Alaska rural, or not from Alaska. The grouping process is to ensure that each group exhibits similar characteristics therefore has the same production function characteristics within the group.[9] CFEC then fills in aggregate daily catch per group for each district for us.

Even though the first data set allows us to observe the number of daily landings in each district by group, we are unable to neither distinguish whether a landing has been made by a single or a double permit vessel nor can we distinguish whether a harvester switches district.[10] Therefore, we complement the first data set with 2010 to 2012 daily individual harvester registration decision from Alaska Department of Fish and Game (ADF&G). This drastically shortens our data estimation time frame from the initial 11 years to 3 years only. Harvesters in Bristol Bay are required to register with ADF&G in a district before they can start fishing in the registered district. The law however does not require a harvester to "withdraw" from a district if a harvester has decided to stop fishing for the season once they have registered. Given this data set, we can observe when a harvester decides to switch district and whether they are registered as a single or double permit operation. However, we are still unable to distinguish whether a harvester has ended their fishing for the season nor can we distinguish whether a harvester has taken a day off from fishing.

With the joint data set, we are still unable to distinguish whether a landing is made by a single or double-permit vessel because we cannot tie an individual harvester's landing directly to

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[9] For instance, a vessel with 700 horsepower with refrigeration system onboard is going to be more productive in catching fish than a vessel with 100 horsepower without refrigeration system. Permit holders who are not from Alaska and Alaska urban citizens usually have better access to credit and therefore implies a higher likelihood of a more productive vessel.

[10] For instance, let's supposed that we observe 4 landings at Ugashik and 0 landings in other districts at t for a group k with 10 vessels. At t + 1, we observe 1 landing at Ugashik and 0 landings in other districts. And at t + 2, we observe 1 landing each for Ugashik and Egegik and 0 elsewhere. Based on the observation, we cannot conclude that a vessel has switched district from Ugashik to Egegik at time t. This is because there is a total of 10 vessels. The Egegik landing could have been made by a vessel who just started fishing at time t. We also cannot say for sure if the landing observed in Ugashik at time t+1 is made by one of the vessels that made landings at time t.

registration data. We can only tie it to the group. Therefore, we will be using the expected number of double versus single permit operation in a group for the estimation. Lastly, we utilize daily catch and escapement data from 2010 – 2012 from University of Washington Alaska Salmon Program. We utilize this dataset to reconstruct daily arrival of fish by district. The average travelling time from fishing district to the counting towers located at each stream is on average: 4 days for Igushik river, 1 day for Wood river, 2 days for Nushagak river, 3 days for Kvichak river, 2 days for Alagnak river, 1 day for Naknek river, 5 days for Egegik river, and 2 days for Ugashik river.[11]

2.3 METHODOLOGY

Given that we only have access to group level daily landings data, we first define a model in which translates group to individual production function. Next, we estimation an individual production function for each district using the joint group level landings data based on the equation derived from the production function model. With the estimated production function per district, we simulate predicted daily predicted catches for 0-hour, 48-hour, and no switching policies in equilibrium. Lastly, we introduce 100 log-normal stochastic shocks to daily arrival of fish in each district.

Individual Harvester Production Function Model

Let's suppose a single-permit vessel's catch yield (h_1) follows a Cobb-Douglas production with number of fish in the district (A), the aggregate horsepower deployed in the district (E), and the vessel's individual horsepower (V) as the only inputs:

$$h_1 = A^{\alpha} E^{\beta} V^{\gamma} \ \ where\ \alpha \in (0,1)\ \&\ \beta < 0\ \&\ \gamma > 0 \quad (2.1)$$

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[11] There are more sophisticated methods of reconstructing daily fish arrival (Cunningham et al. 2015b). However, the reconstruction of such magnitude is beyond the scope of this paper. We did verify our reconstruction method with 2002 – 2008 reconstructed fish arrival data from Curry et al. 2017 paper. Our reconstruction method yields similar daily arrival of fish to Curry et al. (2017) from 2002 to 2008.

α indicates the proportion of fish available caught out of the number of fish in the district. Since proportion of fish caught cannot exceed the proportion of fish available, the coefficient value is restricted between 0 and 1. β captures the congestion externality associated with having too much capital deployed in the district; an additional vessel in the water increases all the other vessels' fishing costs through crowding in the fishing district (Smith 1969).[12] γ captures the individual vessel's productivity on the fishing ground.

Let's suppose that a double-permit vessel (h_2) is more productive with a scale of δ where δ is the efficiency gain in having two rather than one permit onboard:

$$h_2 = A^{\alpha}E^{\beta}V^{\gamma}\delta^{P} \; where \; P = 1 \; if \; double - permit \quad (2.2)$$

In log form, the production function for each type of operation is equal to:

$$\ln(h_1) = \alpha\ln(A) + \beta\ln(E) + \gamma\ln(V) \quad (2.3)$$

$$\ln(h_2) = \alpha\ln(A) + \beta\ln(E) + \gamma\ln(V) + \ln(\delta) \quad (2.4)$$

Assuming homogenous production activity for people within a group, this implies that the group catch, H, is equal to:

$$H = n_1 * h_1 + n_2 * h_2 = n_1A^{\alpha}E^{\beta}V^{\gamma} + n_2A^{\alpha}E^{\beta}V^{\gamma}\delta^{P} = A^{\alpha}E^{\beta}V^{\gamma}(n_1 + n_2\delta^{P}) \quad (2.5)$$

Where n_1 is the number of people in a group catching fish using single permit and n_2 is the number of people in a group catching fish using double permit. In log form, this implies that the log group catch is equal to:

$$\ln(H) = \ln(n_1 + n_2\delta^{P}) + \alpha\ln(A) + \beta\ln(E) + \gamma\ln(V) \quad (2.6)$$

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[12] The opposite of congestion externality is agglomeration effect where an additional vessel in the water reduces all the other vessels' fishing costs. An agglomeration effect implies a positive coefficient on β. Given the common property resources and characteristics of Bristol Bay, an agglomeration effect is very unlikely and therefore be excluded in this paper.

Individual Harvester Production Function Estimation

We estimate a production function for each harvester for each district using the joint group level landings data and reconstruction of daily arrival of fish in each district based on the derivation of equation 2.6. A group i's daily catch at time t for each district j, gc_{ijt}, is a function of daily arrival of fish for each district, a_{jt}, aggregate horsepower for the district, ahp_{jt}, group average vessel horsepower, vhp_{it}, effective number of single permit vessels in a group for each district, n_{ijt}, and year and group level fixed effect (with all the terms in log with the exception of year and group FE):

$$gc_{ijt} = \beta_{0j}a_{jt} + \beta_{1j}ahp_{jt} + \beta_{3j}vhp_{it} + \beta_{4j}n_{ijt} + groupFE_{ij} + \epsilon_{ijt} \quad (2.7)$$

$$where\ j = district\ index;\ \ i = group\ index;\ \ t = time\ index$$

Effective number of single permit vessels is calculated as:

$$n_{ijt} = n_{1,ijt} + \delta_j n_{2,ijt} \quad (2.8)$$

Since we do not have accurate information on the actual exit and entering decision associated with the data set, $n_{1,ijt}$ and $n_{2,ijt}$ are constructed as the expected value of double versus single permit operations in a group for a given day in a district.[13] δ captures how much more effective a vessel is in catching fish using double relative to single permit. We run a panel group fixed effect regression for each district during the period of June 25th to July 16th, during which the 48-hour policy is in effect. We also remove the days in which a district is closed for fishing. All the coefficient estimates and related statistics are recorded in Table 2.1. The estimation period ranges from 2010 to 2012. To nonparametrically estimate δ_j, we run a panel group fixed effect

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[13] We have the total number of single and double permit registrations for a day by district. However, we do not observe "exit" decision from permit registration data. Therefore, we can only calculate an expected number of single permits that made landings based on the observed total landings for the day for the given district. For instance, if we observe 5 double permits and 5 single permits registered for Ugashik district for day 3 but we only observe 4 total landings in Ugashik district on day 3. This means that on expected term, there are 2 single permits and 2 double permits that made a total of 4 landings in Ugashik district on day 3.

regression with different values of δ_j ranging from 1 to 2 for each district and select δ_j in which the sum of square residuals is minimized for district j.[14]

Table 2.1 Coefficient values for each district's production functions and relevant statistics

	Nak-Kvi				Nushagak			
Parameter	Estimate	Std. Error	t-value	Pr(>|t|)	Estimate	Std. Error	t-value	Pr(>|t|)
β_{0j}	0.804	0.012	68.758	0	0.980	0.022	45.389	0
β_{1j}	-0.289	0.032	-9.016	2.65E-19	-0.572	0.042	-13.712	4.54E-42
β_{2j}	1.086	0.108	10.069	1.21E-23	0.074	0.084	0.884	0.37663
β_{3j}	1.113	0.019	57.161	0	1.085	0.019	55.692	0
	Ugashik				Egegik			
Parameter	Estimate	Std. Error	t-value	Pr(>|t|)	Estimate	Std. Error	t-value	Pr(>|t|)
β_{0j}	0.516	0.0153	33.82	2E-16	0.748	0.0168	44.541	2E-16
β_{1j}	-1.083	0.0334	-32.36	2E-16	-0.347	0.0278	-12.509	2E-16
β_{2j}	0.0375	0.151	0.248	0.804	0.296	0.119	2.485	0.013
β_{3j}	1.112	0.0301	36.849	2E-16	0.999	0.024	41.647	2E-16

	Ugashik	Egegik	Nak-Kvi	Nushagak
Adj. R-squared	0.433	0.569	0.629	0.727
Number of observations	3483	3911	5625	5377
δ_j	1.46	1.64	1.35	1.54

Simulation

Given the district-specific individual harvester production function, we then simulate harvester behaviors in equilibrium for three policies, 0-hour, 48-hour, and no switching policies. Each policy differs in the how freely a harvester can switch from a district to another. 0-hour policy is where harvesters can switch districts daily without any penalty. No switching policy is the opposite where harvesters cannot switch district throughout the season. 48-hour policy intends to

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[14] Choices of δ_j are restricted between [1,2] since a double-permit operation cannot be less effective than a single permit and are not twice as effective as a single permit operation from net size perspective. Our estimation of δ_j are also consistent with what we would expect.

imitate the current Bristol Bay 48-hour policy with a slight difference. Due to computational difficulties, we have restricted harvesters in our simulation to only be able to switch district once in comparison to the unrestricted nature of the 48-hour policy observed in Bristol Bay.

We also restrict few vessels to stay inside the same district regardless of the policies. This is intended to understand if homesteader, driftnet vessels who choose to voluntarily stay in a district and never switches, may be impacted differently under different mobility restrictions. The vessels we restrict are identified by the group. We only choose groups with all its vessels that are homesteaders to be our homesteader vessels in the simulation. Their district location choice is also same as what they choose to do under the district registration data. The number of homesteader vessels by district are recorded in Table 2.2.

Table 2.2 Homesteader district choices by year

Year	Ugashik	Egegik	Naknek-Kvichak	Nushagak
2010	3	5	16	16
2011	7	2	11	21
2012	9	7	25	27

The predicted daily catch under simulation is estimated under the equilibrium condition assuming perfect and complete information. Harvesters, knowing that when the district closes and opens each day and what everyone else is doing, selects the district in which maximizes their catch. In equilibrium, no harvesters have incentive to deviate along. To predict equilibrium daily catch for a vessel, we need to first define the choices that each harvester has under each policy. For 0-hour policy, since harvesters, except for homesteaders, choose a district that they want to enter each day, we let d_{lt} be the district choice a vessel l at time t chooses where $d_{lt} \in \{1, 2, 3, 4\} \quad \forall l, t$ with 1 = Ugashik, 2 = Egegik, 3 = Naknek-Kvichak, and 4 = Nushagak. This means that a harvester's predicted catch, $c_{it,l}(d_{lt})$, in each district is a function of aggregate district horsepower conditional on what other vessels choose, their individual vessel horsepower, whether they are registered as a double or single permit operation, and group fixed effect (all in log term except for the group fixed effect and the indicator function):

$$c_{it,l}(d_{lt} = j|d_{-lt}) = \widehat{\beta_{0j}} a_{jt} + \widehat{\beta_{1j}} ahp_{jt}(d_{lt}, d_{-lt}) + \widehat{\beta_{3j}} vhp_{i,l} + \widehat{\beta_{4j}}\left(I^{\delta_j}\right) + group\widehat{FE}_{ij}$$

$$\forall\, j \;\; if \; \sum_{l}^{n} c_{it,l}(d_{lt} = j|d_{-lt}) \le a_{jt} \qquad (2.9)$$

$$c_{it,l}(d_{lt} = j|d_{-lt}) = \frac{\widehat{\beta_{0j}} a_{jt} + \widehat{\beta_{1j}} ahp_{jt}(d_{lt}, d_{-lt}) + \widehat{\beta_{3j}} vhp_{i,l} + \widehat{\beta_{4j}}\left(I^{\delta_j}\right) + group\widehat{FE}_{ij}}{\sum_{l}^{n} c_{it,l}(d_{lt} = j)} * a_{jt}$$

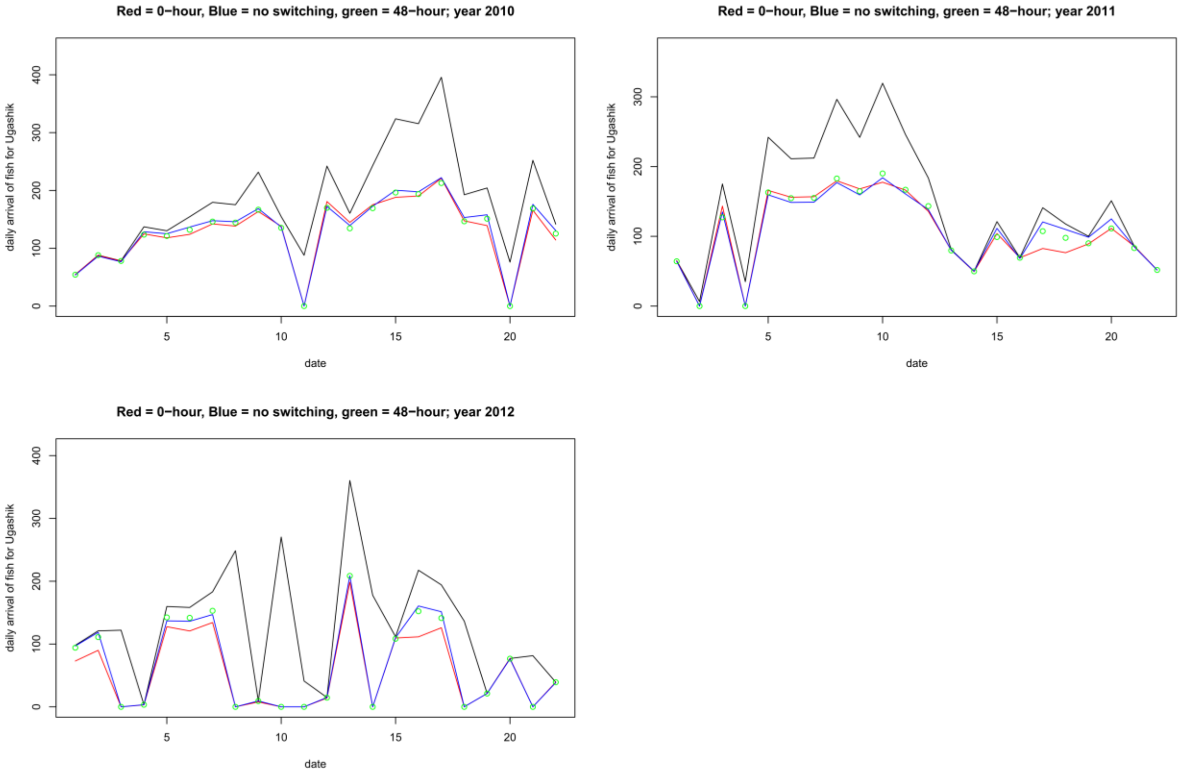
$$\forall\, j \;\; if \; \sum_{l}^{n} c_{it,l}(d_{lt} = j|d_{-lt}) > a_{jt} \qquad (2.10)$$

$$where\ j = district\ index;\ \ i = group\ index;\ \ t = time\ index; l = individual\ index$$

$$I\ is\ an\ indicator\ function\ where\ I = 1\ if\ single\ permit\ opertaion$$

$$= 2\ if\ double\ permit\ operation$$

Since we only had three seasons worth of data to estimate production function for each district, we are not able to estimate a production for Ugashik and Egegik in which captures the situation of low daily run situations. During low run days, aggregate predicted catches often yield higher catches than the number of available fish in the district. Therefore, we apply a rule of multiplying individual predicted daily catch by the ratio of aggregate daily catch to daily run to ensure that number of fish caught do not exceed the number of available fish for catch in the district. Figure 2.1, Figure 2.2, Figure 2.3, and Figure 2.4 record graphs of predicted equilibrium daily catches by year and district and policy.



Red = 0−hour, Blue = no switching, green = 48−hour; year 2010

Red = 0−hour, Blue = no switching, green = 48−hour; year 2011

Red = 0−hour, Blue = no switching, green = 48−hour; year 2012

Figure 2.1. Daily predicted and actual catch (black line) of Ugashik district for each policy by year in thousands of fish

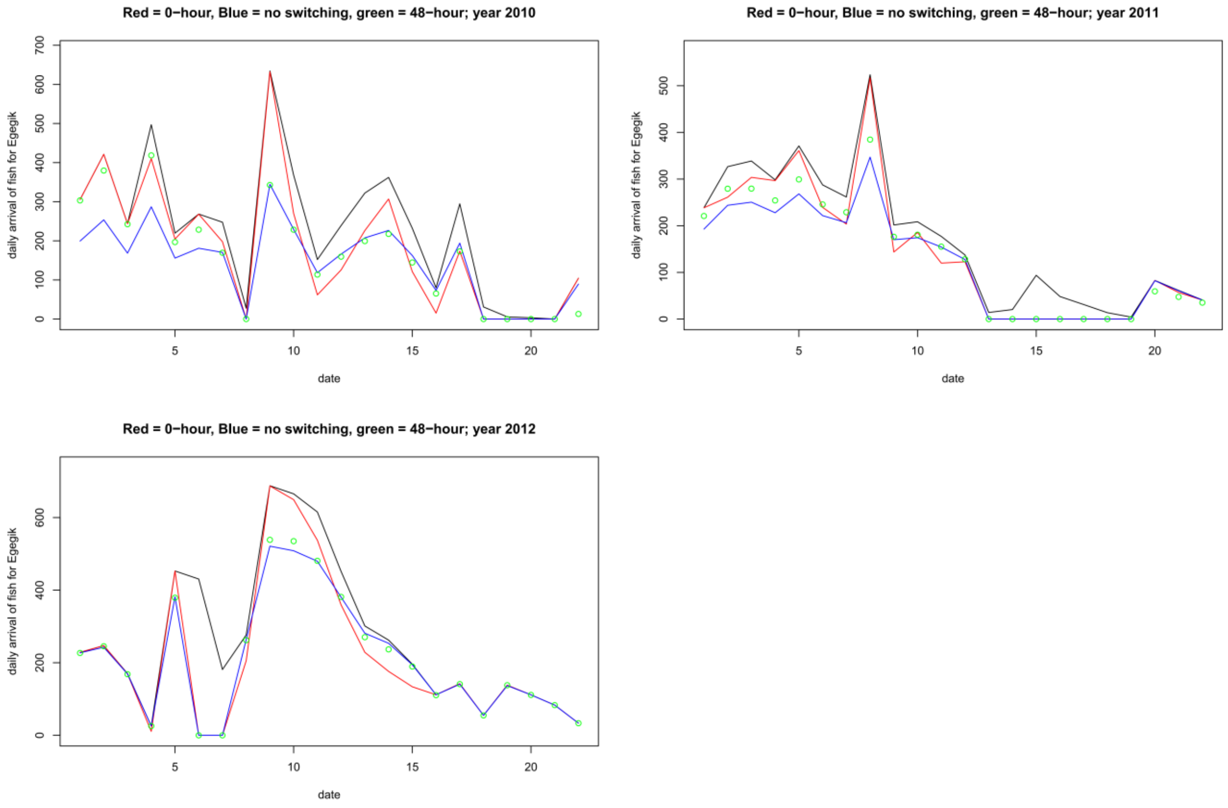


Figure 2.2. Daily predicted and actual catch (black line) of Egegik district for each policy by year in thousands of fish

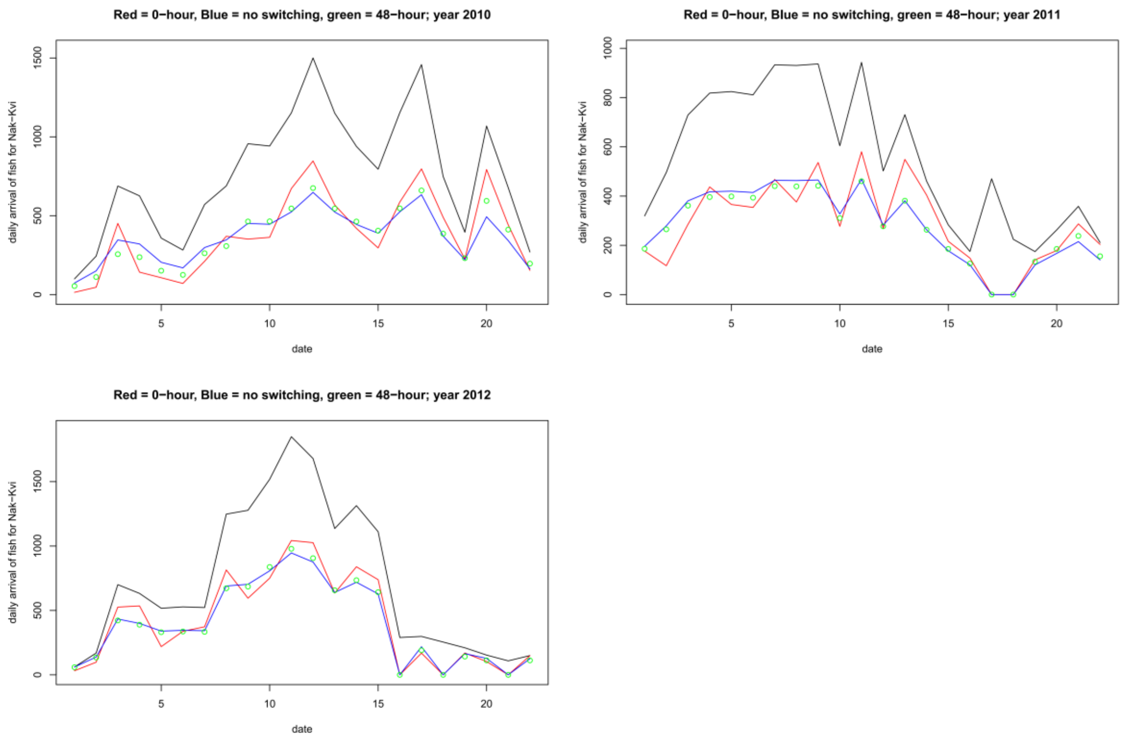


Figure 2.3. Daily predicted and actual catch (black line) of Naknek-Kvichak district for each policy by year in thousands of fish

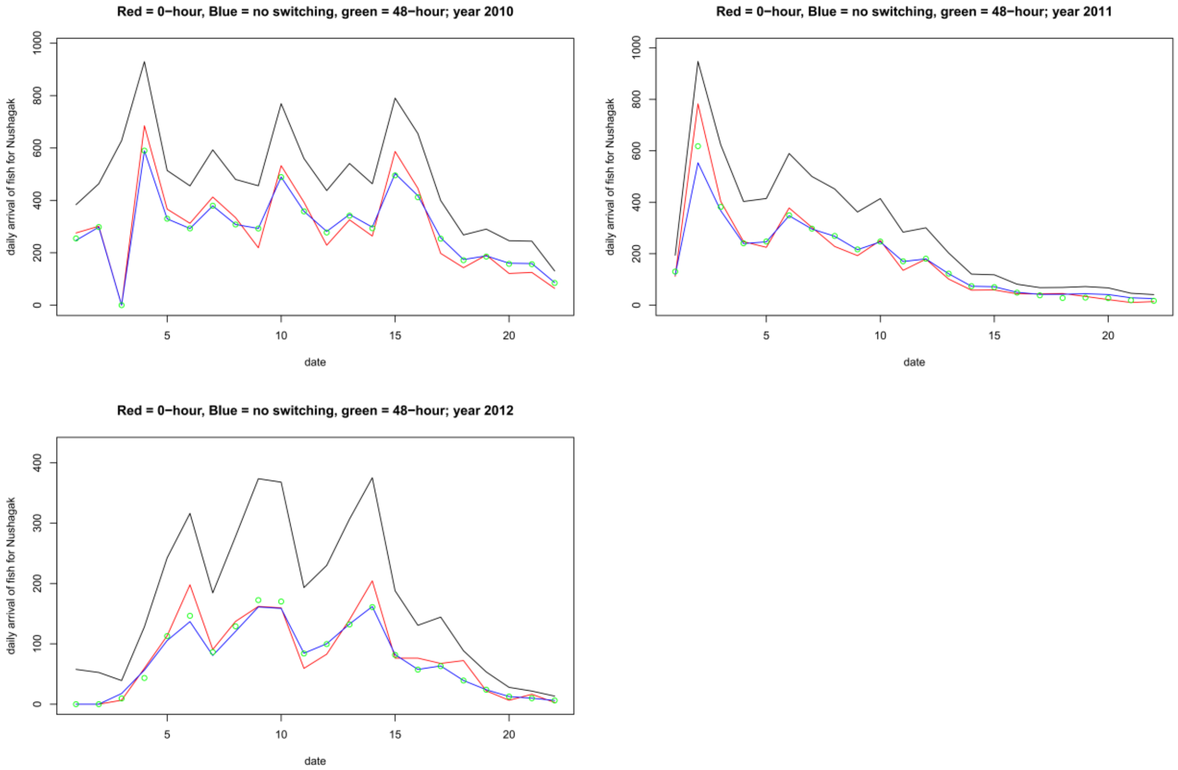


Figure 2.4. Daily predicted and actual catch (black line) of Nushagak district for each policy by year in thousands of fish

For each given day, a harvester l is going to choose district j in which maximizes their predicted catch given what everyone else chooses:

$$\max_{\{d_{lt}\}} c_{it,l}(d_{lt} = j \mid d_{-lt}) \quad \forall t \quad (2.11)$$

Each harvester is going to continue repeating equation 2.11 until $\mathrm{d_{lt}} = j$ no longer varies for each vessel subject to d_{-lt}, meaning that each harvester no longer has the incentive to deviate alone given what everyone else chooses each day.

For no switching policy, the process is lightly different than the 0-hour policy. Instead of maximizing a vessel’s catch each day given everyone else’s action, a vessel maximizes a season worth of catch over one district. The district choices that a vessel has is d_l where $d_l \in$

$\{1, 2, 3, 4\}$ $\forall l$ with the predicted catch calculated as the following with each harvester maximizing:

$$\max_{\{d_l\}} \sum_{t=1}^{22} c_{it,l}(d_l = j \mid d_{-l}) \qquad (2.12)$$

$$c_{it,l}(d_l = j|d_{-l}) = \widehat{\beta_{0j}} a_{jt} + \widehat{\beta_{1j}} ahp_{jt}(d_l, d_{-l}) + \widehat{\beta_{3j}} vhp_{i,l} + \widehat{\beta_{4j}} \left(I^{\delta_j}\right) + group\widehat{FE}_{ij}$$

$$\forall j \;\; if \sum_{l}^{n} c_{it,l}(d_l = j|d_{-l}) \leq a_{jt} \qquad (2.13)$$

$$c_{it,l}(d_l = j|d_{-l}) = \frac{\widehat{\beta_{0j}} a_{jt} + \widehat{\beta_{1j}} ahp_{jt}(d_l, d_{-l}) + \widehat{\beta_{3j}} vhp_{i,l} + \widehat{\beta_{4j}} \left(I^{\delta_j}\right) + group\widehat{FE}_{ij}}{\sum_{l}^{n} c_{it,l}(d_{lt} = j)} * a_{jt}$$

$$\forall j \;\; if \sum_{l}^{n} c_{it,l}(d_l = j|d_{-l}) > a_{jt} \qquad (2.14)$$

Harvesters under no switching policy are going to choose according to equation 2.12 until none of the harvesters have the incentive to deviate alone.

For 48-hour policy, the process is more complicated. Each harvester has 232 potential choices to choose from assuming they can only switch district once during the 22-day district registration period. We implicitly assume that harvesters cannot switch district during the last 2 days since switching during the last two days simply void them the opportunity of fishing on the last 2 days. The earliest day a harvester can switch district is at day 2 since they could have easily chosen a different district to start with if they decide that a district is not a good district to fish in at day 1. This leaves a total of 228 choices with 19 days multiplied by 4 initial districts then multiplied by 3 possible final district choices.[15] Harvesters also have the choice to not switch districts, adding an additional 4 choices. This means that the choices that 48-hour vessels face,

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[15] This is why it is computationally burdensome. Imagine that now harvesters have a choice of switching district twice. The number of possible choices become 19*36 + 19*12 + 4 = 916.

$d_l \in \{1, 2, \dots, 232\}$ each number corresponding to two district choices, from and to, and the time in which the choice to switch district. A complete list of district choices with time is recorded in Table 2.3 and Table 2.4.

Table 2.3 District Choices for the 48-hour policy with starting district in Ugashik and Egegik

$d_l = 1 - 4$ if a vessel decides to not switch district with Ugashik = 1, Egegik = 2, Naknek-Kvichak = 3, Nushagak = 4. 321 is the district short name for Ugashik. 322 is district short name for Egegik. Naknek-Kvichak's district short name is 324. 325 is the district short name for Nushagak. The list of two tables below corresponds to a d_l which indicated the time in which a vessel switches from district x to district y. For instance, $d_l = 185$ means that a vessel switches from Nushagak to Ugashik at time equal to 5.

From 321 to Time	322	324	325	From 322 to Time	321	324	325
2	5	6	7	2	62	63	64
3	8	9	10	3	65	66	67
4	11	12	13	4	68	69	70
5	14	15	16	5	71	72	73
6	17	18	19	6	74	75	76
7	20	21	22	7	77	78	79
8	23	24	25	8	80	81	82
9	26	27	28	9	83	84	85
10	29	30	31	10	86	87	88
11	32	33	34	11	89	90	91
12	35	36	37	12	92	93	94
13	38	39	40	13	95	96	97
14	41	42	43	14	98	99	100
15	44	45	46	15	101	102	103
16	47	48	49	16	104	105	106
17	50	51	52	17	107	108	109
18	53	54	55	18	110	111	112
19	56	57	58	19	113	114	115
20	59	60	61	20	116	117	118

Table 2.4 District Choices for the 48-hour policy with starting district in Nak-Kvi and Nushagak

$d_l = 1 - 4$ if a vessel decides to not switch district with Ugashik = 1, Egegik = 2, Naknek-Kvichak = 3, Nushagak = 4. 321 is the district short name for Ugashik. 322 is district short name for Egegik. Naknek-Kvichak's district short name is 324. 325 is the district short name for Nushagak. The list of two tables below corresponds to a d_l which indicated the time in which a vessel switches from district x to district y. For instance, $d_l = 185$ means that a vessel switches from Nushagak to Ugashik at time equal to 5.

From 324 to Time	321	322	325	From 325 to Time	321	322	324
2	119	120	121	2	176	177	178
3	122	123	124	3	179	180	181
4	125	126	127	4	182	183	184
5	128	129	130	5	185	186	187
6	131	132	133	6	188	189	190
7	134	135	136	7	191	192	193
8	137	138	139	8	194	195	196
9	140	141	142	9	197	198	199
10	143	144	145	10	200	201	202
11	146	147	148	11	203	204	205
12	149	150	151	12	206	207	208
13	152	153	154	13	209	210	211
14	155	156	157	14	212	213	214
15	158	159	160	15	215	216	217
16	161	162	163	16	218	219	220
17	164	165	166	17	221	222	223
18	167	168	169	18	224	225	226
19	170	171	172	19	227	228	229
20	173	174	175	20	230	231	232

For each season (from t = 1 to 22), a harvester l is going to choose a combination of district choices with time, $d_l \in \{1, 2, \dots, 232\}$, to maximize their predicted catch given what everyone else chooses:

$$\max_{\{d_l\}} c_{it,l}\,(d_l \mid d_{-l}) \qquad (2.15)$$

$$c_{it,l}(d_l|d_{-l}) = \widehat{\beta_{0J}}a_{jt} + \widehat{\beta_{1J}}ahp_{jt}(d_l, d_{-l}) + \widehat{\beta_{3J}}vhp_{i,l} + \widehat{\beta_{4J}}\left(I^{\delta_j}\right) + group\widehat{FE_{\iota J}}$$

$$\forall\, j \;\; if \sum_{l}^{n} c_{it,l}(d_l|d_{-l}) \leq a_{jt} \qquad (2.16)$$

$$c_{it,l}(d_l|d_{-l}) = \frac{\widehat{\beta_{0J}}a_{jt} + \widehat{\beta_{1J}}ahp_{jt}(d_l, d_{-l}) + \widehat{\beta_{3J}}vhp_{i,l} + \widehat{\beta_{4J}}\left(I^{\delta_j}\right) + group\widehat{FE_{\iota J}}}{\sum_{l}^{n} c_{it,l}(d_{lt} = j)} * a_{jt}$$

$$\forall\, j \;\; if \sum_{l}^{n} c_{it,l}(d_l|d_{-l}) > a_{jt} \qquad (2.17)$$

Harvesters under 48-hour policy are going to choose according to equation 2.15 until none of the harvesters have the incentive to deviate alone.

It is important to recognize that the assignment process to find d_{lt} $\forall i, t$ is conditional to the initial assignment. The current initial allocation assignment process is random. It is possible that under a different random initial assignment process, a vessel in equilibrium may end up in a different district and thus resulting in a different conclusion. We run three policy simulations under 10 different initial allocation assignment process and find that individual predicted yearly catches are essentially the same with about 5% variations in equilibrium district assignment (Table 2.5). Hence, our results are not sensitive to the initial allocation assignment process.

Table 2.5 Annual predicted catch and district assignment difference with different initial allocation assignment process

	0-hour Policy	No switching policy	48-hour policy
Mean difference in annual predicted catch	-2.3	-2.1	5.8
Absolute mean difference in annual predicted catch	132.9	92.3	110.6
% difference in district assignment	3.8%	6.6%	5.5%

Lastly, we introduce a yearly stochastic shock to each district one hundred iteration. A stochastic shock η_k follows a log normal distribution. The simulated daily arrival of fish $\widehat{a_{jtk}}$ for district j, day t for year k is a product of the actual arrival of fish a_{jtk} for district j, day t, year k and the randomly stochastic shock:

$$\widehat{a_{jtk}} \sim a_{jtk}(1+\eta_k), \eta_{jk} \sim logNorm(0.0204, 0.2184) \quad (2.18)$$

This methodology of introducing shocks to the system is adopted in the Anderson et al. (forthcoming) study to come up with annual preseason forecast river-specific arrival number of fish for Bristol Bay. Table 2.6 records the mean and the standard deviation of 100 simulated arrival of fish in each district by year in comparison to the actual arrivals. All simulated total number of yearly arrival of fish by district graphs are included in Figure 2.5, Figure 2.6, and Figure 2.7.

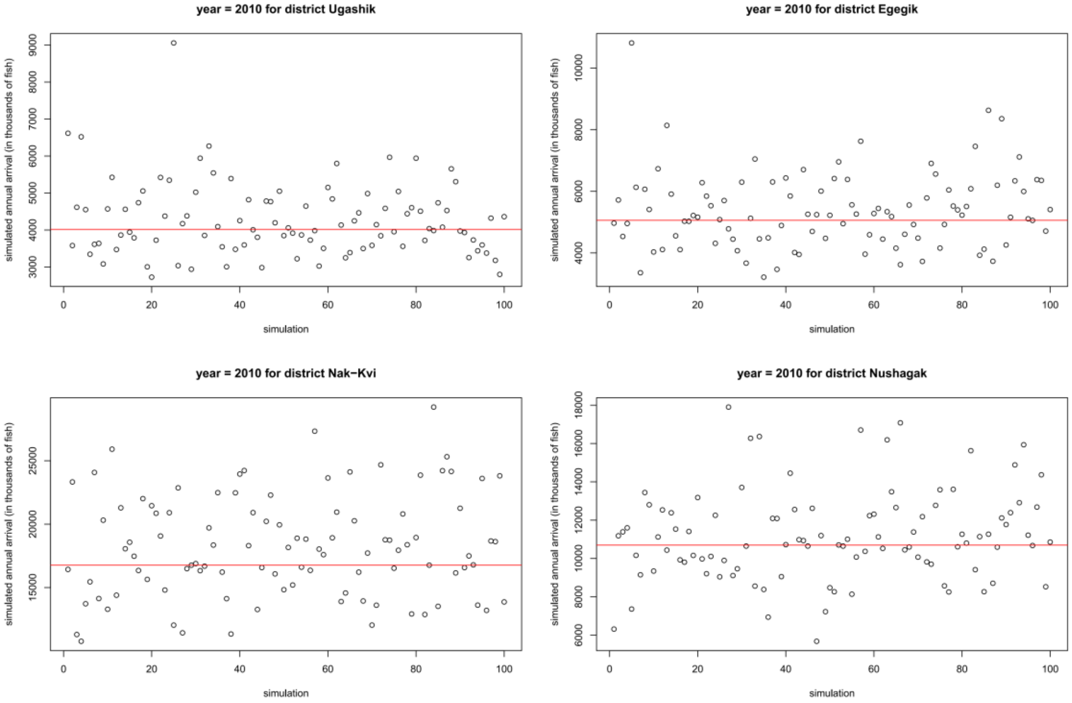

Figure 2.5. 2010 yearly arrival of fish by district for each simulation with red line being the actual yearly arrival of fish for the district

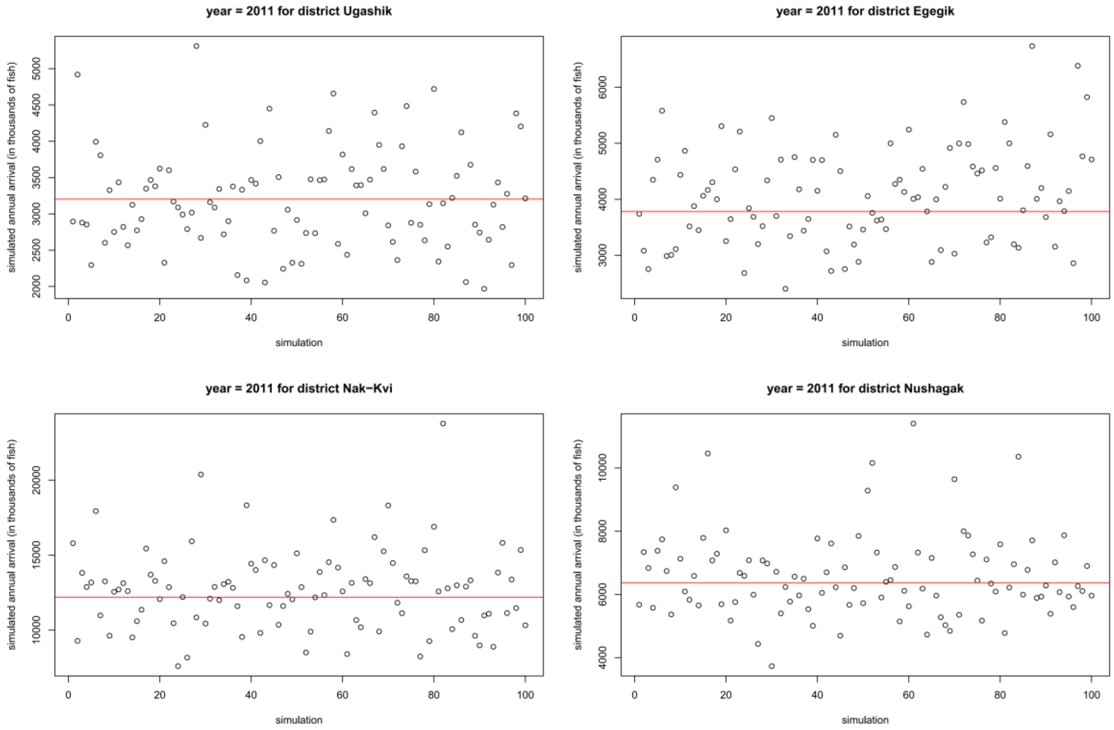

Figure 2.6. 2011 yearly arrival of fish by district for each simulation with red line being the actual yearly arrival of fish for the district

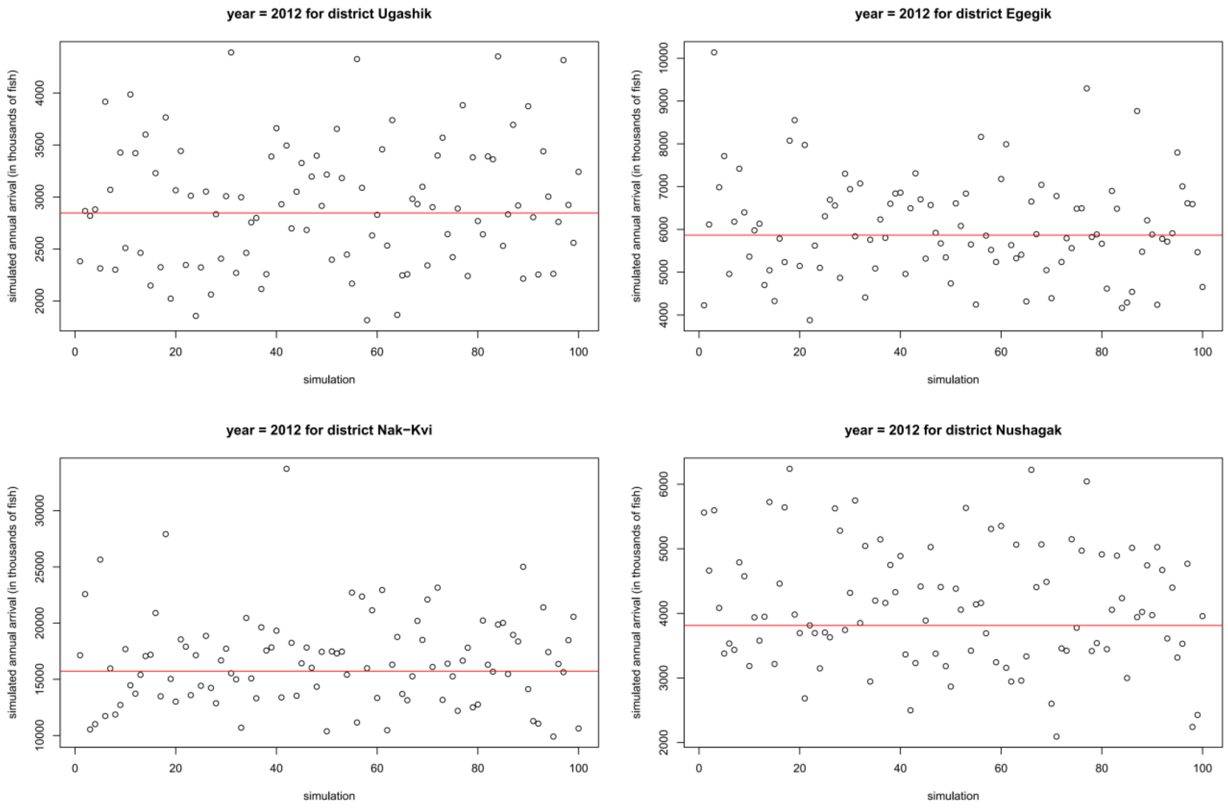

Figure 2.7. 2012 yearly arrival of fish by district for each simulation with red line being the actual yearly arrival of fish for the district

Since the objective is to simulate how harvesters perform under each policy with a stochastic shock to a specific district, harvesters under 48-hour policy can only switch district from its initial district under no stochastic shock. This reduces d_l from initially 232 choices to $d_l \in \{1, 2, \dots, 58\}$. A harvester can begin switching districts starting at date equal to 2. They continue to have the options to switch districts until date equal to 20, giving them 19 days to switch districts. 57 choices (3*19) plus the choice of staying at the initial district gives them 58 options to choose from under 48-hour policy. Harvesters under no switching policy must remain in the same district under no stochastic shock. With 0-hour policy, there are no restrictions under stochastic shock simulations.

Table 2.6 Sample statistics of simulated arrival by year (in thousands of fish)

Year	District	Mean of simulated yearly arrival	Std. Dev. Of simulated yearly arrival	Actual yearly arrival
2010	Ugashik	4,274	989	4,019
	Egegik	5,377	1,237	5,059
	Nak-Kvi	18,227	4,016	16,764
	Nushagak	11,204	2,374	10,698
2011	Ugashik	3,197	683	3,204
	Egegik	4,066	859	3,781
	Nak-Kvi	12,678	2,682	12,199
	Nushagak	6,583	1,321	6,371
2012	Ugashik	2,924	595	2,847
	Egegik	6,044	1,184	5,867
	Nak-Kvi	16,615	4,059	15,724
	Nushagak	4,119	930	3,813

2.4 RESULTS

We first begin examining results without any stochastic shocks. We find that daily aggregate predicted catch difference between two policies in a district is very similar across three policies. The differences range from -9,000 to 22,000 fish per day on average. Given the scale of daily catch in Bristol Bay that ranges from few thousand to over a million fish in a district per day, the differences are small. This is consistent with the characteristics of Bristol Bay that fishing power is sufficient. Even the highest restriction in mobility, no switching policy, do not reduce daily aggregate catch significantly.

Similar aggregate daily catches also translate to similar aggregate yearly catch across three policies. In comparison to the actual year aggregate catch by district, it does seem that the simulation model is not predicting catches for Ugashik and Egegik well. This might be an artifact of how the daily arrival of fish is constructed. Ugashik and Egegik districts often catches a portion of Naknek-Kvichak district's fish because of the geography. Therefore, our estimation of daily arrival of fish is a proxy of the actual available of fish in the districts on Eastside. Therefore, a more meaning way of examining the aggregate yearly catch in comparison to the actual yearly catch is to look at Eastside as a whole. When doing so, the aggregate catches are very similar between a policy and the actual catch observed. All the summary statistics related to district-wide daily and yearly predicted catches are recorded in Table 2.7, Table 2.8, and Table 2.9.

Table 2.7 The mean daily catch difference between two policies in a district

	District	Mean
0-hour – no switching policy	Ugashik	-5.01
	Egegik	21.59
	Nak-Kvi	14.97
	Nushagak	4.46
0-hour – 48-hour policy	Ugashik	-3.38
	Egegik	12.69
	Nak-Kvi	17.11
	Nushagak	3.93
No switching – 48-hour policy	Ugashik	1.63
	Egegik	-8.90
	Nak-Kvi	2.14
	Nushagak	-0.53

*Unit: thousands of fish

Table 2.8 Aggregate catch by district in thousands of fish from simulation and actual catch

Year	District	0-hour	No switching	48-hour	Actual Catch
2010	Ugashik	2,836	2,928	2,858	2,997
	Egegik	4,088	3,227	3,597	3,567
	Nak-Kvi	8,417	8,084	8,094	8,023
	Nushagak	6,526	6,455	6,424	6,668
2011	Ugashik	2,315	2,376	2,352	2,045
	Egegik	3,173	2,768	2,975	2,862
	Nak-Kvi	6,370	6,163	6,039	6,709
	Nushagak	3,868	3,787	3,824	3,983
2012	Ugashik	1,253	1,430	1,417	2,024
	Egegik	4,760	4,601	4,612	4,123
	Nak-Kvi	9,150	8,703	8,675	8,570
	Nushagak	1,753	1,611	1,640	1,890

Table 2.9 Yearly aggregate catch % difference by district relative to the actual catch

Year	District	0-hour	No switching	48-hour
2010	Ugashik	-5.4%	-2.3%	-4.6%
	Egegik	14.6%	-9.5%	0.8%
	Nak-Kvi	4.9%	0.8%	0.9%
	Nushagak	-2.1%	-3.2%	-3.7%
2011	Ugashik	13.2%	16.2%	15.0%
	Egegik	10.9%	-3.3%	3.9%
	Nak-Kvi	-5.0%	-8.1%	-10.0%
	Nushagak	-2.9%	-4.9%	-4.0%
2012	Ugashik	-38.1%	-29.4%	-30.0%
	Egegik	15.4%	11.6%	11.9%
	Nak-Kvi	6.8%	1.6%	1.2%
	Nushagak	-7.2%	-14.7%	-13.2%

Next, we look at how an individual vessel perform across different policies. We calculate the mean and variance of catch differences per individual vessel between two different policies. 0-hour policy yields highest individual yearly catch, with on average catching 512 more fish and 607 more fish than the 48-hour and no switching policy respectively. On average, harvesters catch 95 more fish under 48-hour relative to no switching policy. Less mobility, in equilibrium, implies a lower catch for a vessel. Table 2.10 and Figure 2.8 record summary statistics and graphs for an individual vessel under each policy. Table 2.10 and Figure 2.9 record summary statistics and graphs of an individual vessel's yearly catch differences between two policies.

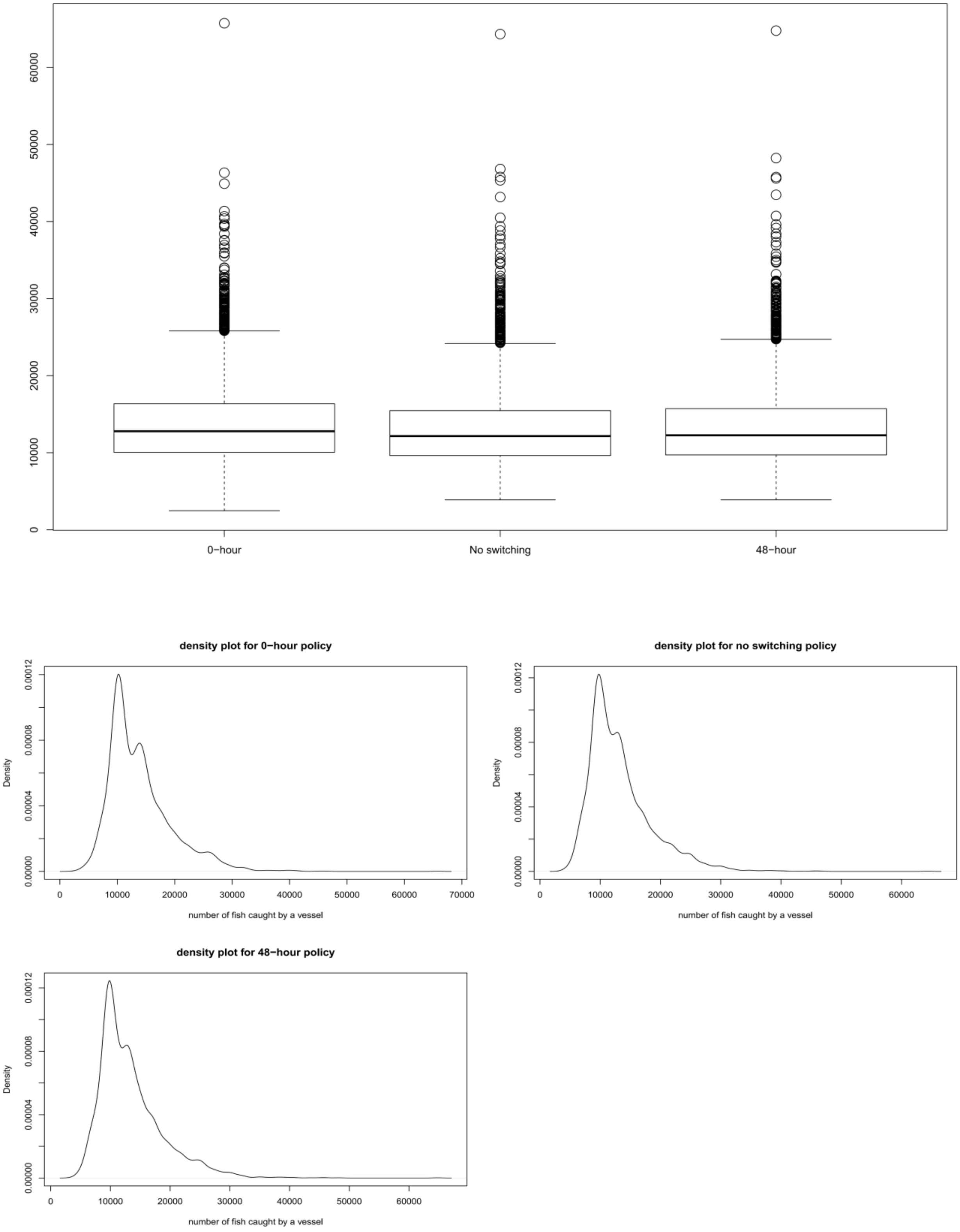

Figure 2.8. Box plots and histogram of an individual vessel’s yearly catch under each policy

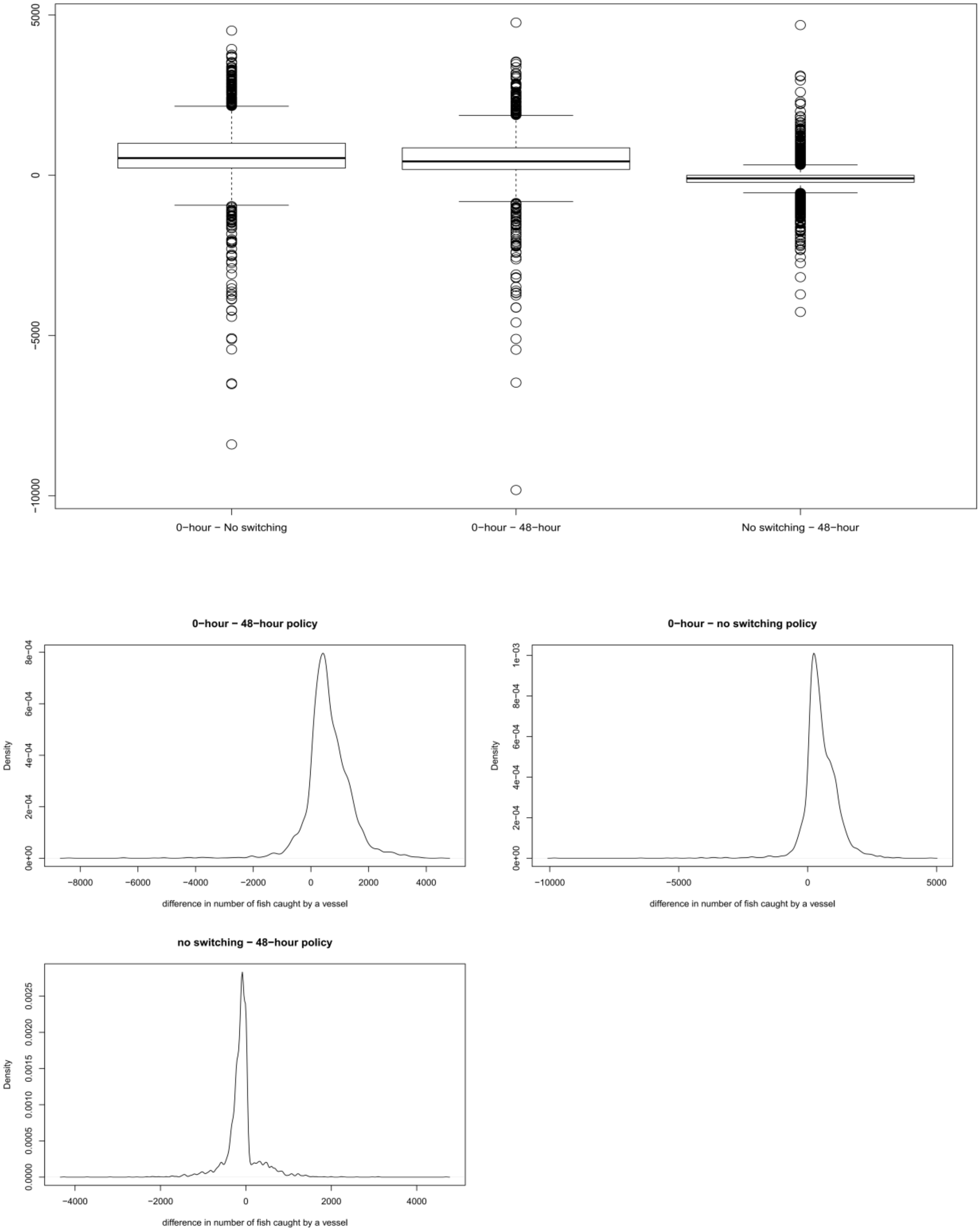

Figure 2.9. Box plots and histogram of an individual vessel’s yearly catch differences between two policies

Table 2.10 Average vessel yearly catch under each policy and catch differences between two policies in number of fish

	Mean	Std. dv.
0-hour policy	13,931	5,545
No switching policy	13,323	5,307
48-hour policy	13,419	5,372

	Mean	Std. dv.	% deviation mean	% deviation std. dv
0-hour – no switching policy	607.36	809.82	4.55%	6.16%
0-hour – 48-hour policy	511.94	686.53	3.85%	5.26%
No switching – 48-hour policy	-95.42	425.27	-0.57%	3.20%

With stochastic shocks to the run, the pattern we observe from without stochastic shock continues with widen variance. First, we examine the aggregate catch by district for a year across all simulations for all policies. Overall, 0-hour policy catches the most fish per district, followed by 48-hour and no switching policy. In some years and districts, 48-hour policy do better than the 0-hour policy. The graphs are recorded in Figure 2.10 and Figure 2.11.[16]

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[16] For Ugashik 2012, there is a big noticeable gap between the 48-hour policy to 0-hour and no switching policy. However, the gaps are merely a result of scaling. Ugashik gap between the 48-hour and the 0-hour policies is approximately 1 to 1.5 million of fish in 2012. For Egegik and Naknek-Kvichak districts, the gaps between the 0-hour and the 48-hour polies ranges from 1.5 to 2 million fish and 1 to 3 million of fish respectively.

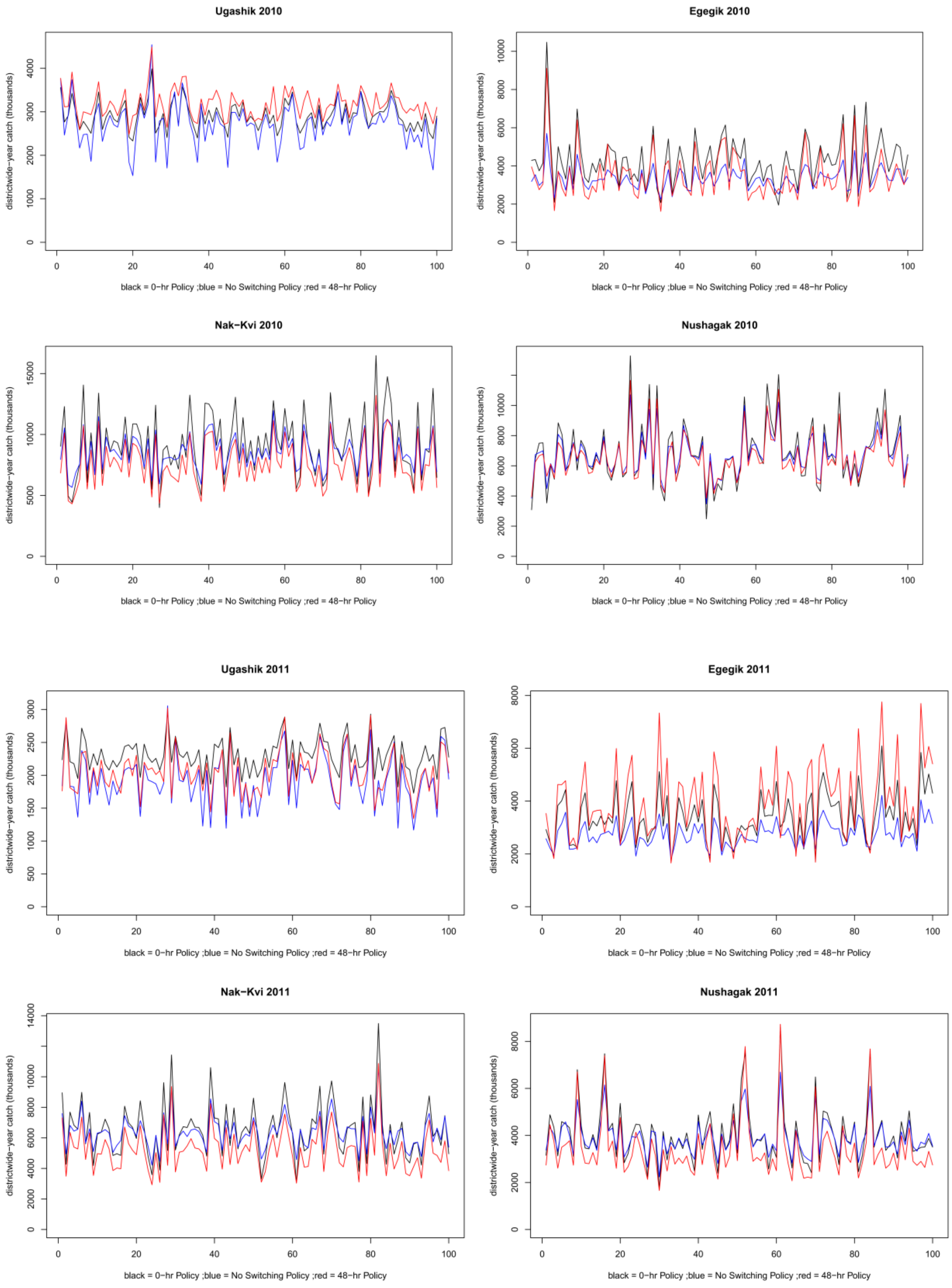


Figure 2.10. Aggregate catch by year and district for all simulations – 2010 and 2011

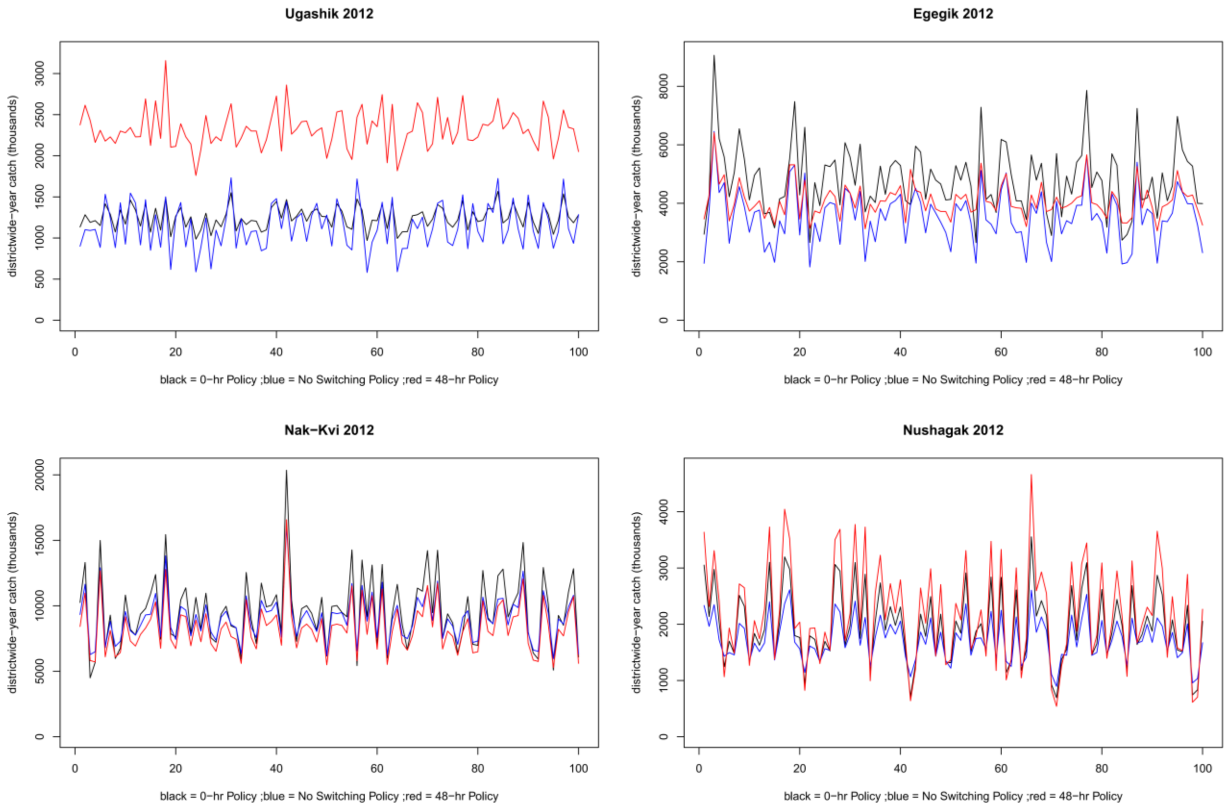


Figure 2.11. Aggregate catch by year and district for all simulations – 2012

Next, we calculate the average performance of a vessel across all simulations for a policy. We find that harvesters under 0-hour policy now catches on average 1,327 and 1,162 more fish than the no switching and 48-hour policy respectively. In comparison to average catches without stochastic shock, 0-hour policy harvesters do significantly better under stochastic shocks. 48-hour policy harvesters perform similarly. Harvesters under no switching policy are worse off with the introduction of stochastic shocks. This is consistent with what we set out to test. Mobility restriction effort control policies shift some district-specific shocks to harvesters. Table 2.11 and Figure 2.12 record summary statistics and graphs for the average catch of an individual vessel across all simulations for each policy.

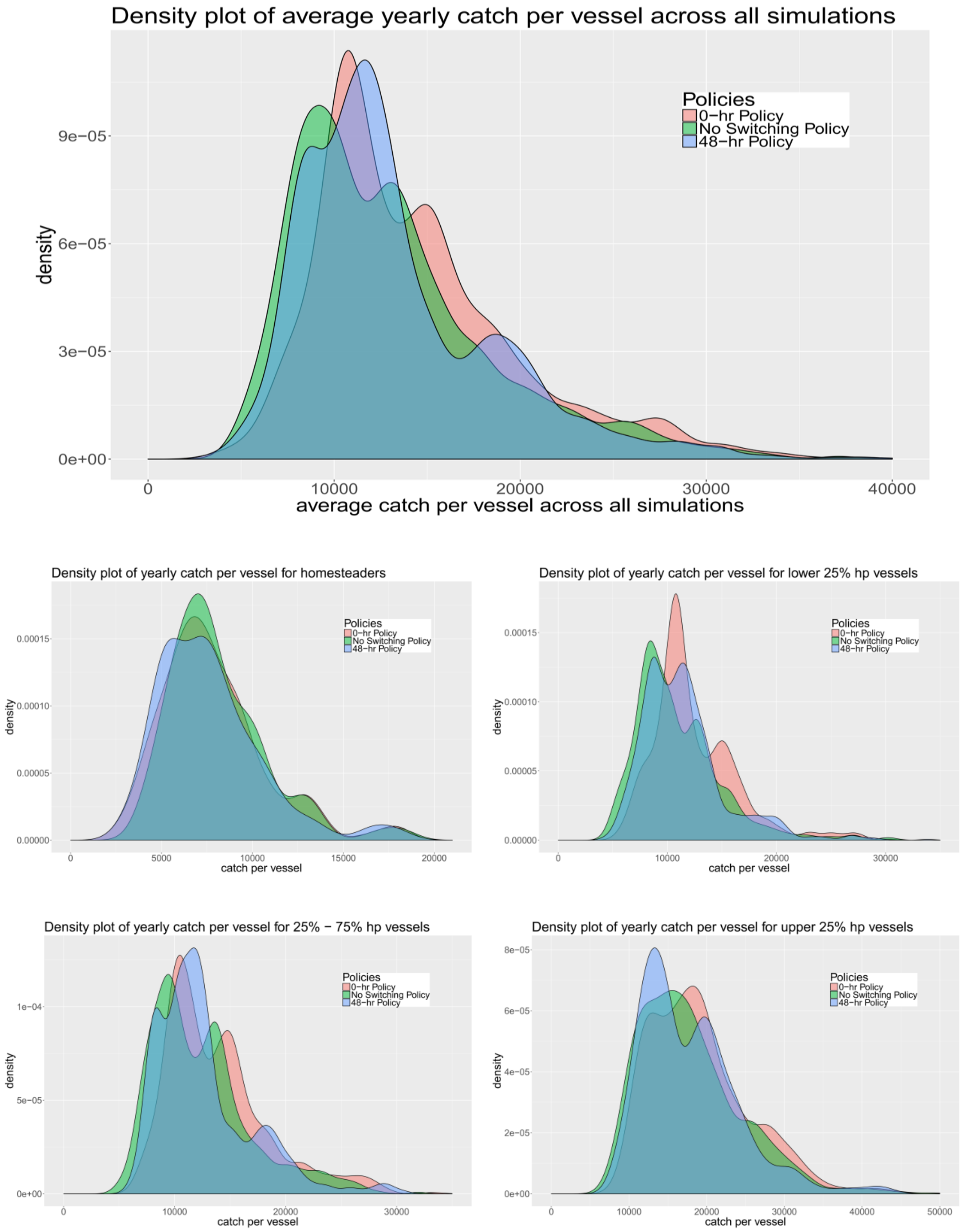


Figure 2.12. Density plot of average yearly catch per vessel across simulations by vessel type

Table 2.11 Average vessel yearly catch across all simulations under each policy and catch differences between two policies in number of fish

	Mean	Std. dv.	Semi-var
0-hour policy	14,579	5,833	2,212,741
No switching policy	13,252	5,819	18,021,929
48-hour policy	13,417	5,658	6,713,515

	Mean	Std. dv.	% deviation mean	% deviation std. dv
0-hour – no switching policy	1327.33	1192.97	12.07%	12.97%
0-hour – 48-hour policy	1162.23	1611.53	9.79%	11.66%
No switching – 48-hour policy	-165.10	1882.24	-0.92%	14.17%

We also calculate semi-variance that each harvester, l, experiences under each policy, p, by calculating the difference between predicted yearly catch under stochastic simulation k, $c_{l,pk}$, relative to their predicted yearly catch without stochastic shocks, $\overline{c_{l,p}}$:

$$semivariance_{l,p} = \tilde{\sigma}_{l,p}{}^2 = \frac{1}{n}\sum_{\overline{c_{l,p}} > c_{l,pk}}^{n} (\overline{c_{l,p}} - c_{l,pk})^2 \qquad (2.19)$$

Semi-variance is a finance term to only look at the negative fluctuations of an asset. In this application, we want to focus specifically on the downside risks that each harvester may experience under each policy. Calculating semi-variance allows us to focus our attention on the downside risks. Semi-variance is the highest for no switching policy, followed by 48-hour policy, with the least for 0-hour policy. This is consistent with the restrictions on mobility.

Lastly, we examine whether the impact of stochastic shock distributes evenly across all types of vessels. We break down vessel type into three different groups: homesteaders, vessels with horsepower less or equal to 260 (25% horsepower quantile) excluding homesteaders, and vessels with horsepower equal or more than 450 (75 % horsepower quantile) excluding homesteaders. Upper 75% horsepower vessels catch the most fish, followed by lower 25% horsepower quantile vessels, with homesteaders performing the worse across all policies. Homesteaders are composed mainly of lower vessel horse power vessels, supported by the 50% horsepower quantile of homesteaders is equal to 25% horsepower quantile of non-homesteaders. Table 2.12 and Figure 2.12 records summary statistics and graphs by vessel type for all three policies.

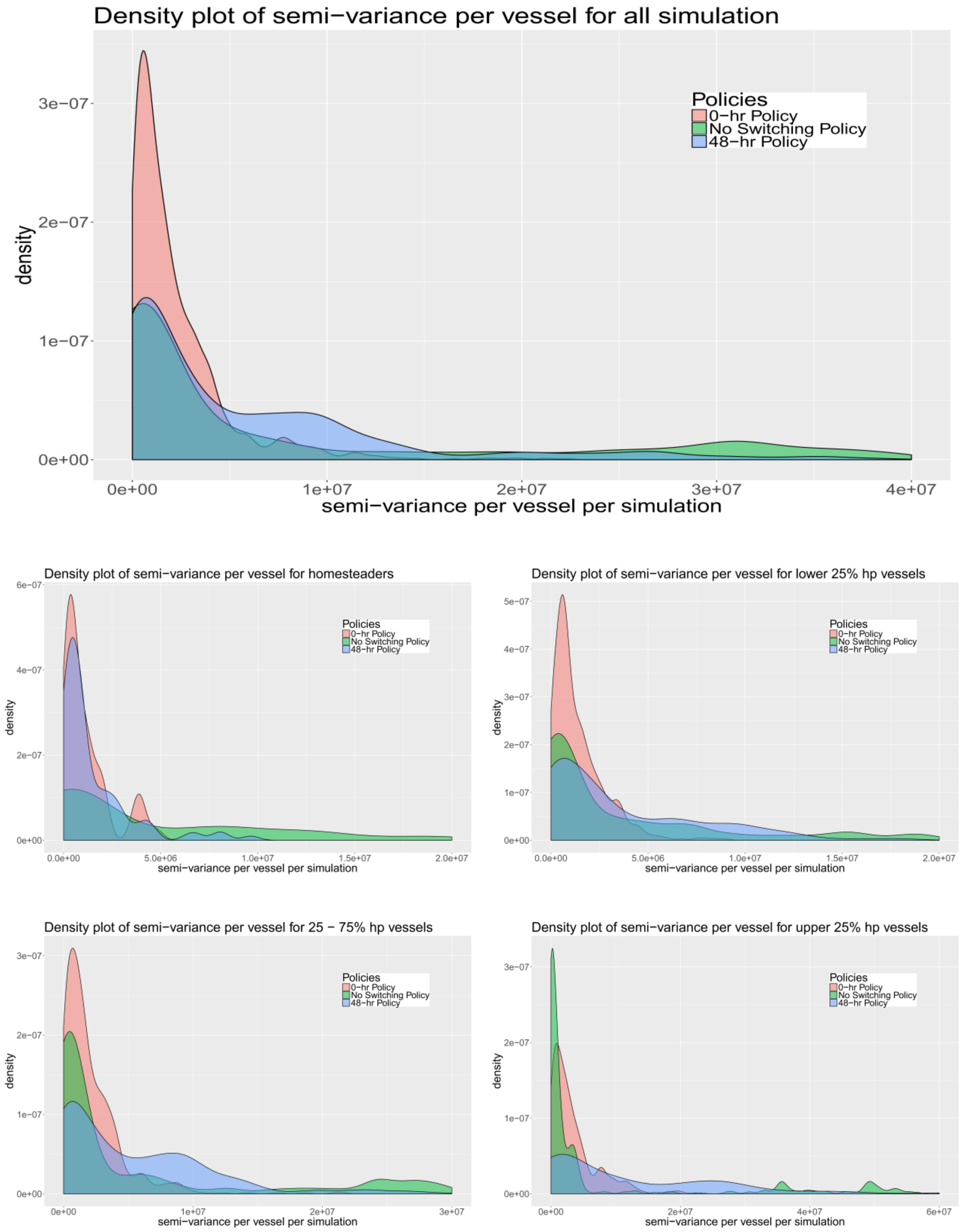
Table 2.12 Summary statistics of average catch across all simulation by policy and vessel type and quantile of horsepower for homesteaders versus non-homesteaders

Vessel type	Homesteaders		<= 25% HP quantile		>= 75% HP quantile	
Number of vessels	149		1069		965	
Policy	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
0-hour	7,850	2,904	12,497	4,077	19,209	6,710
No switching	8,114	2,731	11,025	4,271	17,944	6,716
48-hour	7,653	2,893	11,462	4,167	17,857	6,568

Horsepower Quantile	25%	50%	75%
Homesteaders	210	260	320
Non-homesteaders	260	330	450

Across policies, average catch is highest under no-switching policy, followed by 0-hour and 48-hour policies for homesteaders. When there is a higher than expected run to a district, harvesters under no switching policy cannot switch to that district, leaving harvesters, including homesteaders, who have chosen that district to benefit from the unanticipated higher return. Under 0-hour and 48-hour policies, homesteaders face competitions from harvesters who can switch into the district experiencing higher than expected runs, are worse off on average relative to no switching policy. For non-homesteaders, 0-hour policy yields the highest return with no switching and 48-hour policies yielding similar returns. The homesteaders, the higher the horsepower, the gap difference between 0-hour policy and the other two policies. Higher the horsepower with higher degrees of flexibility in switching leads to better outcomes for mobile harvesters.

To capture downside risks that each harvester faces, we also plot density plot of semi-variance per vessel for each simulation calculated based on equation 2.19 (Figure 2.13). On average, 0-hour policy harvesters have the lowest semi-variance, followed by 48-hour policy. No switching policy harvesters face the highest semi-variance with a much fatter tail than other two policies. Breaking down harvesters by vessel type, no switching policy vessels have much fatter tails than other two policies.



* Thin right tails of the density graphs have been truncated in order to present these density graphs clearly.

Figure 2.13. Density plot of average semi-variance per vessel across simulations by vessel type

Table 2.13 Regression analysis report

	Dependent variable: log(yearly catch)		Dependent variable: Yearly Catch
log(horse power)	0.401*** (0.006)	Horse power	14.39*** (0.185)
No switching policy	-0.108*** (0.006)	No switching policy	-1,327*** (94.3)
48-hour policy	-0.087*** (0.006)	48-hour policy	-1,162*** (94.4)
Homesteaders	-0.461*** (0.013)	Homesteaders	-4,881*** (202)
Constant	7.430*** (0.033)	Constant	12,627*** (112)
Observations	11,739	Observations	11,739
R-squared	0.497	R-squared	0.482
Year Fixed Effect	Yes	Year Fixed Effect	Yes

*p<0.1; **p<0.05; ***p<0.01; standard error is in the prentices.

	Dependent variable: log(yearly catch)		Dependent variable: Yearly Catch
log(horse power)	0.401*** (0.006)	Horse power	14.390*** (0.185)
No switching policy	-0.114*** (0.006)	No switching policy	-1,390*** (96.2)
48-hour policy	-0.090*** (0.006)	48-hour policy	-1,200*** (96.2)
Homesteaders	-0.398*** (0.006)	Homesteaders	-5,767*** (349)
Homesteaders*(no switching policy)	0.160*** (0.032)	Homesteaders*(no switching policy)	1,654*** (493)
Homesteaders*48-hour policy	0.064** (0.032)	Homesteaders*48-hour policy	1,003** (493)
Constant	7.433*** (0.033)	Constant	12,660*** (112)
Observations	11,739	Observations	11,739
R-squared	0.498	R-squared	0.483
Year Fixed Effect	Yes	Year Fixed Effect	Yes

*p<0.1; **p<0.05; ***p<0.01; standard error is in the prentices.

Our findings are backed up by regressing log(yearly catch) and yearly catch with log(horsepower) (or horsepower), year fixed effect, policy types, and whether or not a vessel is mobile or homesteader. Holding everything else constant, being a homesteader reduces a vessel's yearly catch by 4,881 fish. Higher horsepower leaders to higher catch. No switching policy reduces a vessel's yearly catch by 1,327 fish with 48-hour policy reducing a vessel's yearly catch by 1,162 fish relative to 0-hour policy. Table 2.13 records the regression results.

2.5 DISCUSSION

We set out to test whether mobility effort control policies may expose harvesters to district-specific run variability that they could have otherwise avoided under simulation. Using Bristol Bay as the basis of our simulation model, we tested three policies, 0-hour, 48-hour, and no switching policy, varying in the degrees of harvester mobility control. We find that in equilibrium without stochastic shock, harvesters catch the most under 0-hour policy, followed by 48-hour policy, with no switching policy performing the worse. In the absence of any stochastic shocks, harvesters who can switch freely can rush into a district that is experiencing higher run size and avoiding a district that is currently experiencing low run size and or district closure. Under 48-hour policy, harvesters have some degrees of freedom to avoid low run size or districts that are closed for a long period of time. However, due to district switching costs and one time switching restrictions, 48-hour policy harvesters cannot completely avoid district specific risks.

With introduction of district-specific yearly stochastic shocks, the performance gap between policies widens with rankings remain the same. Under no switching policy, harvesters choose their district based on "forecast" and are unable to change districts regardless of realized stochastic shocks. No switching policy homesteaders are able to take advantage of this relative to other policies since other vessels cannot rush into a district that is experiencing higher than expected run. However, mobile harvesters under no switching policy are worse off relative to other two policies. In the case where a district is experiencing lower than expected run, mobile no switching policy harvesters cannot move to other districts, resulting in lower catches. On the other hand, mobile 0-hour policy harvesters can avoid districts that are experiencing lower than expected runs and enjoying the benefits of districts experiencing higher than expected runs, resulting in significantly higher average catches than the 48-hour and no switching policies.

We calculate semi-variance per harvester-policy, a measure of the dispersions of all simulations that fall below the predicted catch without stochastic shocks, to understand the downside risks that harvesters face under each policy. When we only look at average catches across all simulations for a policy, the upside risks mitigate some of the downside risks. No switching policy harvesters face the highest semi-variance, followed by 48-hour, with the least faced by 0-hour policy. This indicates that no switching poly harvesters face the highest downside risks given its inflexibility in switching.

There are many methods to improve upon the current model. Due to data feasibility constraint, we are unable to estimate individual production function based on individual district choice over time. We are also unable to accurately estimate the low run individual catch for Ugashik and Egegik since we only have three years' worth of data. Due to computational constraints, our model restricts the number of times a vessel can switch under 48-hour policy to once. This is a tighter restriction than the policy implemented in Bristol Bay. It would be more realistic to estimate equilibrium catch of 48-hour policy by relaxing such constraint. Nevertheless, the 0-hour policy is our way to put an upper bound estimation to the effects of mobility restriction policies on individual harvesters under 48-hour policy. Another aspect of the model that can be improved upon is the full integration of manager, biological, and economic model. Anderson et al. (forthcoming) has demonstrated the importance of incorporating different aspects of a fishery in evaluating effectiveness of a fishery policy.

Chapter 3. A LABORATORY EVALUATION OF POST-EXCHANGE PRICING AS A MECHANISM FOR RISK SHARING

Abstract

While prices are agreed upon at the time goods are exchanged in most markets, goods in some commodity markets are exchanged with an agreement to establish prices later. Such post-exchange pricing may reduce prices since suppliers have forfeited their leverage. However, we argue that when buyers are uncertain of the eventual value of the project, post-exchange pricing creates a channel for buyers to share risks with suppliers, and buyers may pay an implicit risk premium through higher prices. Therefore, while post-exchange pricing may lead to lower prices than price-at-exchange if product values are known, the risk sharing hypothesis implies higher prices if product values are uncertain. We test this hypothesis with a controlled laboratory experiment, calibrated to the Bristol Bay sockeye salmon fishery, where $400 million of salmon is transferred from harvesters to processors each year under post-exchange pricing mechanism. When wholesale demand schedules are known (uncertain) to buyers, prices are lower (higher) under post-exchange pricing relative to price-at-exchange, consistent with the risk sharing hypothesis. Repeated interactions inhibit buyers' setting zero prices and breaking down the market, and thus is crucial in supporting the post-exchange pricing mechanism.

3.1 INTRODUCTION

"In mainstream economic theory, the firm and the market, for the most part, are assumed to exist and are not themselves the subject of investigation." (Coase, 1988)

In most markets, prices are agreed upon at the time goods are exchanged. Examples of the price-at-exchange mechanism includes stock markets, auctions, consumer retail transactions, etc. Economists have studied such mechanism extensively and they generally agree that imperfect competition under the price-at-exchange mechanism leads to higher prices and result in lower consumer and total surplus. A notable exception is the Bertrand paradox, which states that *two* firms in a homogenous market competing over price is enough to generate Walrasian competitive outcome (Bertrand 1883). Although well-known and studied, price-at-exchange is not the only pricing mechanism observed in a market place. For instance, consignment shop makes agreements with goods' owner and pay the owner only as and when the goods are sold. The consignment shops usually set the sale price of the goods and take a percentage revenue share of the goods sold.[17]

While price-at-exchange pricing is also observed for most trades between harvesters and processors in fisheries, the Bristol Bay sockeye salmon and the Australia Western rock lobster fisheries have adopted post-exchange pricing mechanism.[18] In Bristol Bay, a harvester signs a contract with a processor guaranteeing the delivery of all his catch prior to the beginning of a fishing season. In return, processors will provide their harvesters with non-cash benefits such as boat storage, bunk, and prompt off-loading of catch. After the end of the frenetic fishing season, processors initiate price offers to their harvesters. Harvesters share information about prices being offered by different processors, and processors offer "bonuses" that raise the effective price; processors offering low prices will have difficulty contracting a fleet the following season. The

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[17] Goods that are not sold within a period of time are returned back to the owner. Ownership of those goods remains under the original owner until the goods are sold. Consignment shops usually make recommendation on the price of the good subject to owner's willingness to sell.

[18] The final total payment received by harvesters in the Australian Western rock lobster fishery is a combination of beach price (price paid-at-exchange) and the loyalty bonus determined at the end of the season (Brolos News 2013 and personal communications with George Kailis).

final ex-vessel price is usually determined around Thanksgiving, months after the end of the season.

Two arguments are presented for why this unusual system has arisen. Some argue that the pricing environment is enforced by the processors to promote tacit collusion. Post-exchange pricing adjustment allows processors to know what has been offered, and to coordinate on low prices. This is an argument also supported by the price-at-exchange literature where improved transparency on the producer side helps to facilitate collusion (Schultz 2005 and Harrington 2012). In addition, that different processors offer similar ex-vessel prices has been used to substantiate such a claim, and was at the center of a $900M anti-trust lawsuit "Alakayak et al, vs. All Alaska Seafoods" filed in 1995.[19]

On the other hand, that different buyers pay the same price is also a property of a Bertrand market. Others argue that post-exchange pricing serves both Bristol Bay processors and harvesters by allowing them to share stock and wholesale market demand risks through continuation of updating ex-vessel prices post-season, as products are sold at wholesale.[20] In exchange for waiting until uncertainty is resolved before competing over prices, harvesters receive higher ex-vessel prices because processors do not need to extract a risk premium.

Economics lacks a theory of how pricing mechanisms arise, or models that predict when buyers or sellers control the selection of these mechanisms. Therefore, we evaluate whether post-exchange pricing can serve as a risk-sharing mechanism using a controlled economic experiment,

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[19] The lawsuit was originated in 1991 Bristol Bay salmon fishery where harvesters had alleged processors of price-fixing. The processors were found not liable in a conspiracy of price fixing between 1991 to 1995 in 2003. Plaintiffs' arguments during the price fixing lawsuits included a significant drop in harvesters' share of processor margins during the alleged time of price fixing, similar ex-vessel prices offered across major processors, and the easy-to-collude pricing environment in Bristol Bay. Refer to Knapp (2006) for more details.

[20] The stock uncertainty risk arises from high variability of catch. Most product forms produced in Bristol Bay, canned and headed and gutted, are usually sold months after production. This is where the wholesale market demand uncertainty originates from.

with the price-at-exchange mechanism as an empirical benchmark. The price-at-exchange mechanism incentivize processors to compete over the *current* market share whereas the post-exchange pricing is competition over the *future* market share. Since risk is key to the argument being tested, we vary the level of wholesale market risk processors bear. We also examine the extreme case of post-exchange pricing mechanism where processors only interact once with harvesters to study the importance of repeated interactions. Since the one-shot post-exchange pricing processors have neither the current nor the future catch share as incentives to motivate them to pay, they will pay zero dollars to harvesters regardless of risks.[21] Therefore, the one-shot game post-exchange pricing mechanism provides us another benchmark in evaluating how processors value future catch share and how that plays in supporting the (repeated) post-exchange pricing mechanism.

In the absence of risks, processors, knowing that harvesters can sell their fish to their competitors easily, will offer the Bertrand price to harvesters under the price-at-exchange mechanism to compete for current market share.[22] Bertrand pricing, depending on the model assumptions, can vary from Walrasian to standard Cournot solutions (Edgeworth 1925; Kreps and Scheinkman 1983; Dastidar 1995). In particular, Reinhorn and Weninger (1999) and Weninger (1999) show the existence of pure Nash Equilibrium (NE) solution when the number of competing oligopolistic firms is sufficiently large and the equilibrium prices are near the firm's marginal valuation of inputs based on Bristol Bay environmental characteristics.[23] Given the ranges of

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[21] The one-shot post-exchange pricing mechanism is a two-stage game. At stage 2 where processors decide what to pay to harvesters, processors will choose to pay zero since harvesters have already delivered their fish. At stage 1, harvesters will choose not to participate given they know that processors will not pay at stage 2.

[22] Since many fisheries' ex-vessel markets are oligopolistic markets, we focus our analysis on markets with few buyers and many sellers competing on prices.

[23] The pricing mechanism, even though is supposed to evaluate based on Bristol Bay, resembles the price-at-exchange rather than the post-exchange mechanisms described in this paper.

possible Bertrand prices, we refer to the prices yielded under the price-at-exchange mechanism as Bertrand price rather than one specific possibility.

Post-exchange processors, on the other hand, may have little incentives to compete for current market share since they are already in possession of the fish. However, processors who wish to continue to operate in the future still need to keep prices competitive relative to the opponents to maintain future market share. Any harvesters who receive lower prices from their contracted processors this season will contract with higher-paying processors in future seasons. At one extreme, a one-time participant in a post-exchange mechanisms should pay zero to harvesters, since they do not need to worry about future market catch share in addition to pricing post-delivery. Maintaining future market share, then, drives competitive pricing for the post-exchange mechanism, while maintaining current market share drive competition in the price-at-exchange mechanism in the absence of risks. Depending on the discount rate, post-exchange pricing may yield lower prices than price-at-exchange with one-time post-exchange pricing yielding the lowest prices.[24]

With wholesale market risks, the ex-ante best prices may be lower than ex post best prices, especially if processors are risk averse. This is important because price-at-exchange processors set an ex-vessel price which locks them into a lottery over profit while post-exchange processors avoid the lottery. Depending on what processors pay in the case of no risks, the results from cases with risks can either support or reject the risk-sharing hypothesis assuming common discount rate and risk attitude.

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[24] We are not refuting the possibility that processors may collude under the post-exchange pricing mechanism. In fact, the price-at-exchange pricing mechanism is also subjected to the possibility of collusion with oligopsony market structure if Bertrand price yields positive profit. Holding everything else equal, the main difference between two pricing mechanisms in the absence of risks is current versus future market shares. Collusion factor can easily be integrated into one of the determinants for the discount rate.

Since relative rankings of prices from the price-at-exchange and the post-exchange pricing in the absence of risks depend upon how processors value the future, the risk-sharing hypothesis only applies to certain cases when the risk is presented. Assuming processors pay the same price under both mechanisms in the absence of risks, the risk-sharing hypothesis predicts that the post-exchange processors pay higher ex-vessel prices when risks are presented. Alternatively, if price-at-exchange processors pay higher prices than the post-exchange pricing processors regardless of risks, it is either that the common discount factor is low and/or risk attitude is low, in which risk-sharing hypothesis provides no additional insight to the post-exchange pricing mechanism.[25] In particular, if both the one-shot and repeated post-exchange processors pay same ex-vessel prices, the collusion argument is better supported. The case in which provides the strongest evidence towards risk-sharing hypothesis is where we observe the price-at-exchange processors paying lower (higher) prices than the post-exchange pricing when (no) risks are presented in the wholesale market. In addition, this case is further strengthened if we observe the one-shot post-exchange processors paying the lowest prices out of the three pricing mechanisms under both risk and no risk situations.

We conduct a controlled laboratory experiment, where University of Washington undergraduate student subjects play the role of buyers and suppliers, to test whether the post-exchange mechanism can yield prices consistent with risk-sharing hypothesis. The experiment is calibrated to the Bristol Bay salmon fishery. The experiment design includes three pricing mechanisms, post-exchange, price-at-exchange, and one-shot game post-exchange, with two

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[25] This also applies to the case in which processors in both mechanisms pay the same ex-vessel prices in the absence of risks and the price-at-exchange processors pay higher ex-vessel prices than the post-exchange processors under uncertainty.

conditions, wholesale market demand schedule certainty and uncertainty.[26] There are two hypotheses we are testing in the experiment:

H1: Facing certainty in the wholesale market, the (repeated game) post-exchange yields lower or same ex-vessel prices than the price-at-exchange mechanism. Conditional on the outcome of the certainty case, the (repeated game) post-exchange yields higher ex-vessel prices than the price-at-exchange mechanism with uncertainty in the wholesale market.

H2: One-shot game post-exchange pricing yields lowest ex-vessel prices regardless of risk conditions.

There are many obstacles in testing these hypotheses empirically and theoretically. First, results from analyzing changes in the Bristol Bay ex-vessel prices are biased due to endogeneity issue. Both the wholesale market demand and supply from within the fishery and the rest of the world affect the ex-vessel price of fish. Therefore, it is difficult to establish a counterfactual for the price-at-exchange and the one-shot game post-exchange pricing mechanism. Even if endogeneity is resolved with econometric techniques, data required to conduct empirical analysis may not exist because it would require private information from harvesters and processors. Last but not least, theories have focused primarily on the price-at-exchange pricing mechanism. Although we can tweak the existing models to fit the post-exchange pricing mechanism under some conditions, a formal theoretical analysis on the selection of pricing mechanisms have not been done thus far.

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[26] To simplify the complexity of the experiments, we design the experiments to reflect only the wholesale market uncertainty, which allows us to isolate the effect of uncertainty across mechanisms more easily. If risk-sharing is the key to explain post-exchange pricing in Bristol Bay, more uncertainties would yield better results than our experiment design here.

Through conducting controlled laboratory experiments, it allows us to create and analyze the hypotheses under a manageable condition without loss of generality.

Our focus is on whether future market share can be as competitive as the current market share with risks to test the risk-sharing hypothesis. To reduce chances of future market share having influences on the price-at-exchange mechanism, we model such mechanism using the double-auction mechanism in the experiment.[27] Double-auction mechanism minimizes the force of future market share influencing players' decisions as a result of repeated albeit not intentional interactions between players under the experiment setting (Smith 1981; Ledyard and Moore 1994).[28]

The post-exchange pricing mechanism can lead to higher prices than the price-at-exchange pricing mechanisms when there are uncertainties in the market. We run random effect model controlling for unique individual of a session with session fixed effect to test out our hypotheses. We find that processors pay $0.56 more under the price-at-exchange than the post-exchange pricing mechanism in the absence of risks, suggesting a discount value associated with the future catch share. With risks, processors pay $1.35 less under the price-at-exchange than the post-exchange pricing mechanism. Facing a lottery, the price-at-exchange processors are not willing to pay as much. The implicit risk premium not only covers the risk attitudes but also the discounted value difference between future and current catch share. Lastly, we examine the price difference between the one-shot and the repeated post-exchange pricing mechanisms to evaluate the importance of future catch share. Comparing the one-shot with the repeated post-exchange pricing mechanism, processors pay $1.57 and $2.7 less under certainty and uncertainty condition.

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[27] Double-auction experiment is where both buyers and suppliers actively participate in pricing and purchasing or selling of a good.

[28] Tacit collusion is nevertheless a possibility under both pricing mechanisms. However, we are interested in studying the relative prices between two mechanisms rather than investigating the collusion hypothesis, whether collusion occurs or not is less critical.

We also test out whether end-game and learning phase effects changes our supports in the hypotheses. We find that although the main conclusions stay consistent, the coefficient value for the total number of harvesters participating changes from significant to insignificant. The main driver in yielding positive significant coefficient value under the best model seems to be the learning phase. In an equilibrium state, both harvesters and processors have no incentive to change their behavior unilaterally. Therefore, processors do not have an incentive to pay more (less) to encourage more (less) harvesters from participating.

The rest of the paper is organized as the following: the design of the experiment is first outlined with the results reported in section 2 and 3. Discussion of the experimental results in the last section concludes the paper.

3.2 EXPERIMENT DESIGN

The experiments were conducted in a computer laboratory via a computer program called z-Tree (Fischbacher 2007). We recruited 13 participants from University of Washington undergraduate students for each session. Each participant receives 7 dollars if they show up for the session. Exactly how much they earn depends on their performance during the experiment. A total of 10 sessions were conducted, with average payout of 27 US dollars per student.

At the beginning of each session, participants are randomly assigned a role, either as a buyer or a producer. There are three buyers (processors) and ten producers (harvesters) each period.[29] As producers, they must decide whether to produce and sell the product at an ex-vessel price. As

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[29] We select three buyers to reduce collusive behaviors between firms that may be an artifact of what we are trying to test while maintaining the Bristol Bay sockeye salmon fishery characteristics. Huck, Norman, and Oeschssler (2004) have shown that three firm oligopolies tend to produce output at the Nash level. On the other hand, Fouraker and Siegal (1963) demonstrate that Cournot triopoly exhibits rivalistic rather than tacit collusive behaviors. Under constant marginal cost Bertrand competition, Dufwenberg and Gneezy (2001) have shown that three competitors predict the Bertrand solution well. Though due to our increasing marginal cost structure, it is not clear whether any collusive behaviors may occur with 3 buyers.

buyers, they must decide how many units of products to purchase at some ex-vessel price(s) to sell them at a wholesale price after processing. The key treatment variables are whether the wholesale price is known at the time of the trade and whether the ex-vessel price is set at the time of trade or after the product exchange.

Each supplier needs to make a production decision each period. If they decide to produce, each producer receives one indivisible unit of good to sell with zero value if they fail to sell the good by the end of the period. If they choose to not produce, they receive a reservation wage according to a random initial assignment. Reservation wage schedule is in Table 3.1 with each possible reservation wage value assigned to two producers. Each buyer can purchase up to five goods each period. The constraint on the number of goods purchased mimics the processing capacity Bristol Bay processors face. Each good a buyer purchased requires a processing fee. Each additional unit purchased requires a higher processing fee than the previous unit except for the first one. Quasi-fixed cost with increasing marginal cost schedule is designed to reflect the nature of production in Bristol Bay.[30] Table 3.2 shows the complete cost processing schedule each buyer faces.

To earn money, buyers sell their purchased good(s) in the wholesale market. The wholesale price of the market is randomly selected each period. There are two possible states to the wholesale price, forecast and realized, with 3 possible forecast wholesale prices and each forecast of wholesale prices is associated with 7 possible realized values.[31] A forecast wholesale price is

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[30] Remote location of Bristol Bay requires processors to ship all its packing and processing materials from Seattle few months before the season starts. It also requires processors to hire workers and fly them over to Bristol Bay. Hence, the first unit of processing cost is very expensive to mimic the initial startup cost for the season. The second unit of processing fee is significantly lower than the first one because once the system is set up and ready to process, processing an additional fish is going to be cheap. Since the processing plant is fixed in size, costs increase as number of fish processed increased. When the number of fish exceeds the processing capacity in Bristol Bay, processors typically calls in long haul-out to process fish into lower values (which translates into extra costs to the processors) or ship extra fish to processing plants a day or two away from Bristol Bay.

[31] The wholesale price distribution is symmetric with the mean of the distribution equal to the forecast wholesale price.

randomly selected and revealed to all players at the beginning of each period. Under the certainty condition, the forecast is identical to the realized value. Only processors observe the realized wholesale price under the uncertainty condition. Differences in forecast and realize wholesale price is applied to mirror the wholesale market demand uncertainty risk.

Table 3.1. Wage schedule based on conditions, forecast/realized wholesale prices under each condition

Reservation wage	
Conditions	
Uncertainty	Certainty
5.7	3.3
6.2	3.8
6.7	4.3
7.2	4.8
7.7	5.3

	Forecast wholesale Price			
	Probability	10.6	12.5	14.4
Realized Wholesale Price	5%	5.8	7.7	9.6
	10%	6.9	8.8	10.7
	20%	8.5	10.4	12.3
	30%	**10.6**	**12.5**	**14.4**
	20%	12.7	14.6	16.5
	10%	14.3	16.2	18.1
	5%	15.4	17.3	19.2

Forecast Wholesale Price under Certainty
8.2
10.1
12

Table 3.2. Processing cost schedule

Unit	Marginal Cost	Total Cost
0	0	0
1	3.6	3.6
2	0.2	3.8
3	0.9	4.7
4	1.7	6.4
5	3.4	9.8

The timeline for each mechanism within a period is slightly different. For the price-at-exchange mechanism, producers decide whether they want to produce for the period before entering selling stage. Next, buyers and producers buy and sell goods via double-auction mechanism in which participants can offer and bid prices simultaneously. Lastly, individual period profit is revealed to each participant and buyers now observe the realized wholesale price. Under the post-exchange pricing, buyers first offer contracts to producers in which producers can decide whether they want to accept the offer. After the contracting stage, buyers first observe the realized wholesale price prior to decide how much they would like to pay their contracted producers. All participants know how much each buyer pays his or her producers. Lastly, the profits are revealed to each player. Then timing of the game is identical between the one-shot and the repeated post-exchange pricing mechanism. The only difference is that at the end of each period, the ID number of a buyer is randomly reassigned such that producers cannot distinguish buyers from current period with last. Timeline of each pricing mechanism is presented in Figure 3.1.

Profit per period per producer is equal to the price producer obtains from selling their good or their associated wage value if they decide not to produce. Profit per period per buyer is equal to realized wholesale prices multiply by number of goods purchased minus total payments paid to producers minus processing cost, which depends on the number of good bought.

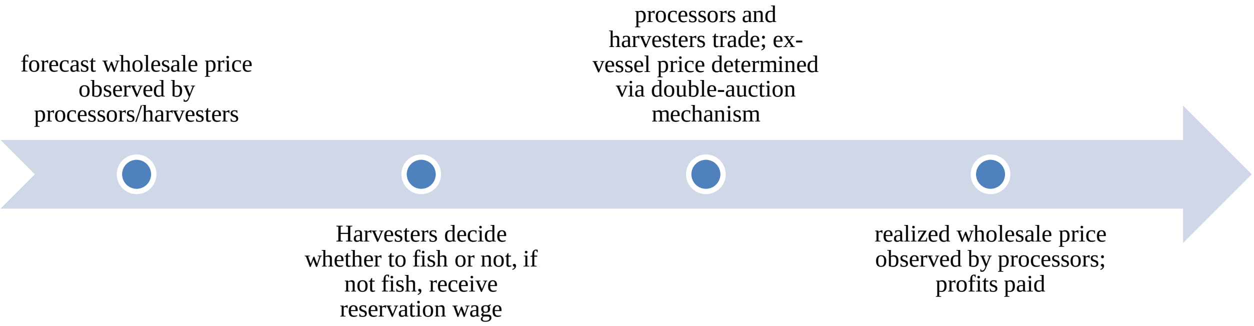

Figure 3.1.a: Price-at-exchange mechanism time line each period

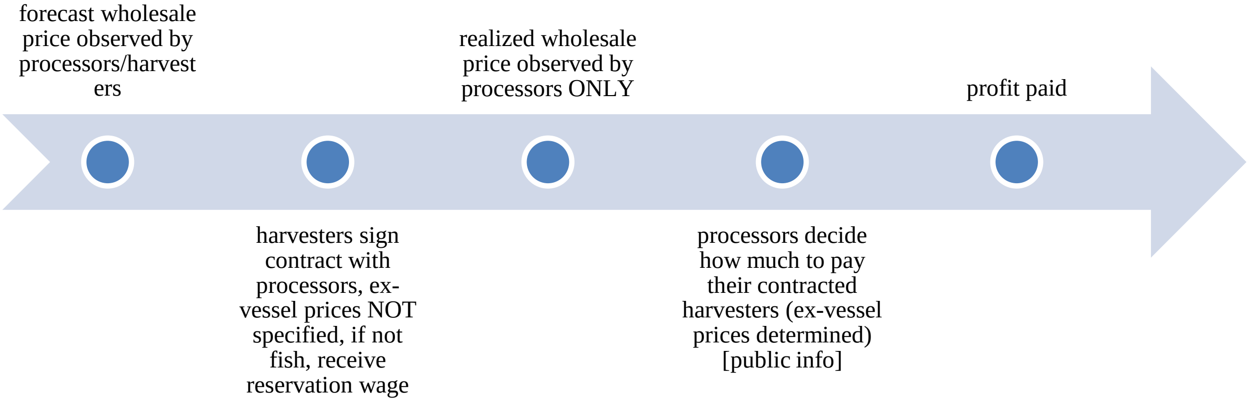

Figure 3.1.b: Post-exchange pricing mechanism time line each period

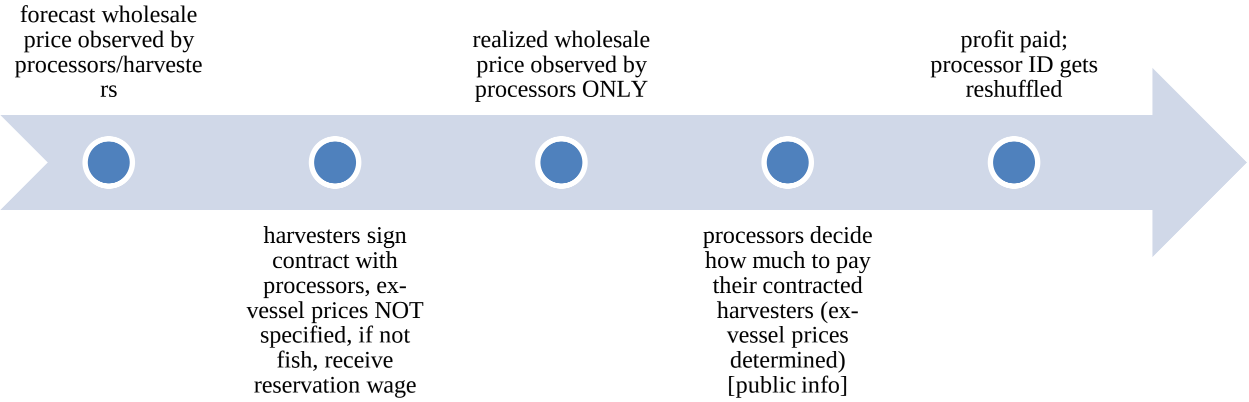

Figure 3.1.c: one-shot game post-exchange pricing mechanism time line each period

Figure 3.1. Timeline of a period for three pricing mechanisms

At the end of each period, both the role and the identification number associated with the role that each participant plays get reshuffled with 15% probability. The game ends with 15%

probability with 0% probability of reshuffling starting from period 19. This is to deal with the end game problems that may occur under repeated post-exchange pricing where buyers may decide to pay zero dollars because they know that the game is ending. A session automatically terminates after period 25.[32] We always run the same pricing mechanism with two different conditions in each experiment session.[33] To avoid any learning behavior from one condition to another, we use two different value set, 1 for certainty and 2 for uncertainty condition. The wages and forecast wholesale prices are 2.4 dollars higher in value set 2 than 1 (see Table 3.1).

3.3 EXPERIMENT RESULTS

We conduct a total of 10 sessions of experiment, with four sessions each for the post-exchange and the price-at-exchange pricing mechanism. For the price-at-exchange and the post-exchange pricing mechanism, we ran three sessions with certainty condition first, followed by uncertainty condition. For the one-shot post-exchange pricing, there was one session with certainty condition first and another with uncertainty condition first. Table 3.3 shows summary statistics by forecast levels, conditions, and pricing mechanism. Figure 3.2 is a bar chart of average ex-vessel price by forecast levels, conditions, and pricing mechanisms.

Summary statistics from Table 3.3 and Figure 3.2 seem to support the hypothesis that one-shot post-exchange pricing yields lowest ex-vessel prices regardless of risk conditions and forecast wholesale price. On average across forecast levels, price-at-exchange processors pay $2.6 dollars more than the one-shot game post-exchange processors whereas post-exchange pricing processors

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[32] Experimental economists have different views on how the termination rule affect experiments involving repeated interactions between a set of players. Normann and Wallace (2012) summarize different points of views and conduct experiments to show that there are no significant differences across views. However, our trial experiments do suggest a strong endgame effect. Hence, we have chosen the current experiment design.

[33] Previous test pilot sessions have shown that switching pricing mechanism within a session may introduce confusions to the participants.

pay $2.8 dollars more under uncertainty condition. Under certainty condition, the one-shot game post-exchange processors pay $3.6 dollars and $1.4 dollars less than the price-at-exchange and the post-exchange pricing processors. Harvester participation is also the lowest for the one-shot game post-exchange pricing, as shown in Figure 3.3. Harvesters, knowing they cannot receive high enough of ex-vessel price under the one-shot game post-exchange pricing relative to their reservation wage, opted not to participate for the seasons.

Table 3.3. Summary Statistics by forecast levels, conditions, and pricing mechanisms

Forecast level	Pricing Mechanism	Price-at-exchange		(repeated) Post-exchange pricing		One-shot post-exchange pricing	
Condition		Uncertainty	Certainty	Uncertainty	Certainty	Uncertainty	Certainty
Low	ex-vessel P	7.021	6.199	6.834	4.196	4.700	2.963
	std. dev.	(1.316)	(0.922)	(2.124)	(2.138)	(4.334)	(2.106)
	number of producers	6.125	8.870	7.083	6.806	4.583	3.313
	std. dev.	(2.669)	(0.856)	(2.710)	(2.559)	(2.882)	(1.626)
Mid	ex-vessel P	8.111	7.160	7.653	4.977	5.694	4.259
	std. dev.	(1.346)	(0.983)	(3.455)	1.840	3.616	3.294
	number of producers	8.517	9.846	8.886	8.000	4.333	5.875
	std. dev.	(1.934)	(0.363)	(1.571)	(1.852)	2.923	1.650
High	ex-vessel P	8.277	8.540	9.406	6.053	5.061	3.828
	std. dev.	(1.671)	(1.210)	(3.120)	(2.185)	4.100	3.103
	number of producers	9.235	9.552	9.308	8.931	5.308	7.176
	std. dev.	(1.036)	(0.818)	(1.302)	(1.237)	2.364	1.438

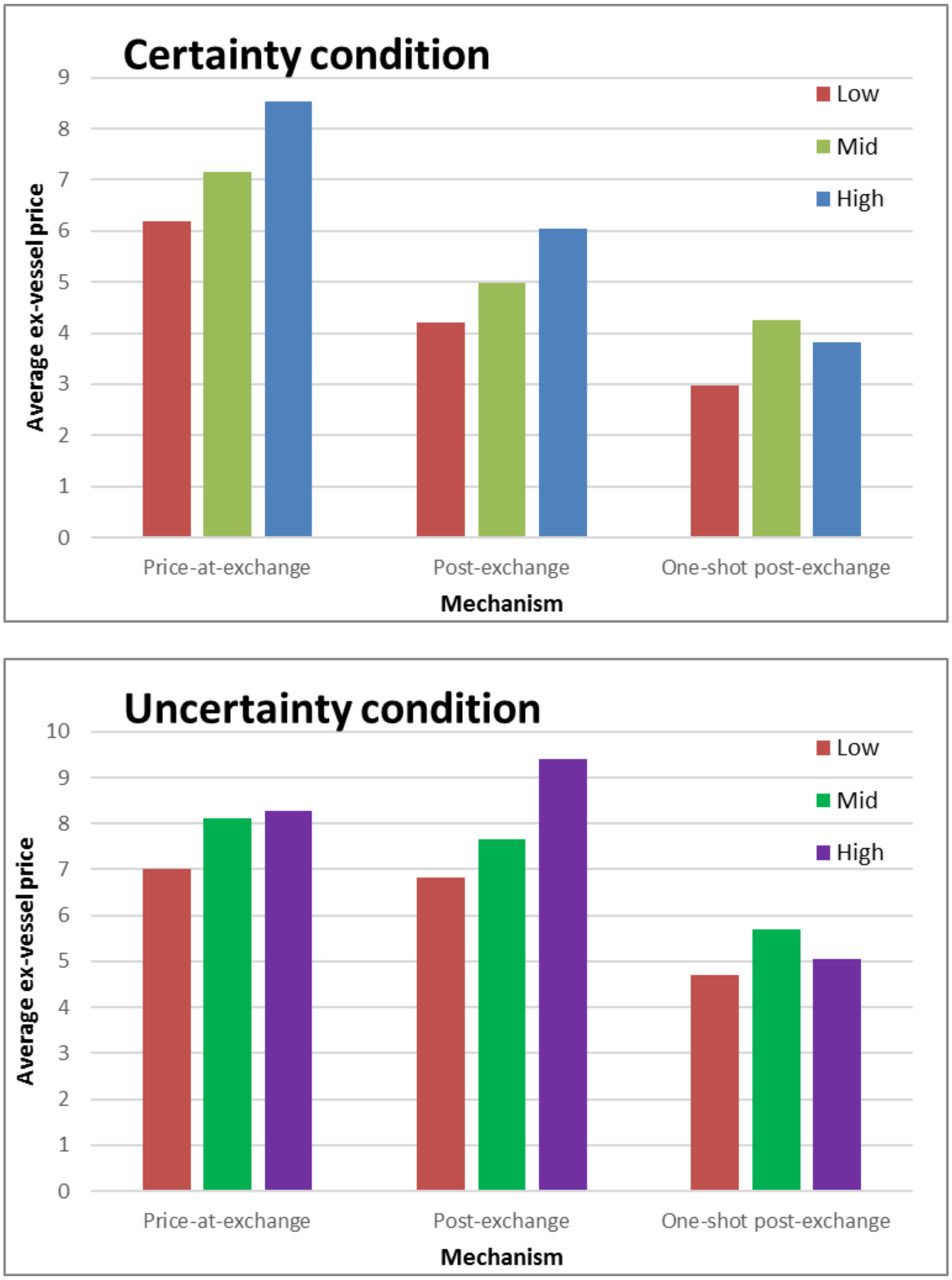

Figure 3.2. Average ex-vessel price by mechanisms and forecast levels under two conditions

However, the Figure 3.2 and Table 3.3 seem to reject the other hypothesis that we are testing—conditional on the certainty condition outcome of relative price ranking between the price-at-exchange and the post-exchange pricing mechanisms whether we find evidence to support the risk-sharing hypothesis. The summary statistics show that price-at-exchange processor pay on average across forecast levels $2.2 dollars more and $0.16 dollars less than post-exchange pricing processors under certainty and uncertainty conditions. On the other hand, the average number of harvesters are higher under the uncertainty condition for the post-exchange relative to the price-at-exchange pricing mechanism as shown in Figure 3.3 and vice versa under the certainty condition. Harvester participation patterns seem to support the risk-sharing hypothesis where more harvesters are participating in the post-exchange pricing mechanism under uncertainty condition and more harvesters are participating in the price-at-exchange mechanism under certainty condition.

Using ex-vessel price as dependent variable, we try to understand how much buyers are willing to pay to producers across different pricing mechanism under each condition. We start with ordinary least square (OLS) including forecast level dummies, pricing mechanism dummies interacting with uncertainty condition dummy as independent variables (regression #1). To isolate individual pricing pattern, we run a random-effect model (REM) (regression #2) controlling for unique personal pricing pattern that is unobservable to us. A unique person is defined as a person who has participated as a buyer within the same session. Both OLS and REM yield the same conclusion suggested by the summary statistics where the one-shot game post-exchange processors pay the least out of three pricing mechanisms across all forecast levels and forecasts. Post-exchange processors pay about the same as price-at-exchange processors when there is uncertainty and pay less under certainty.

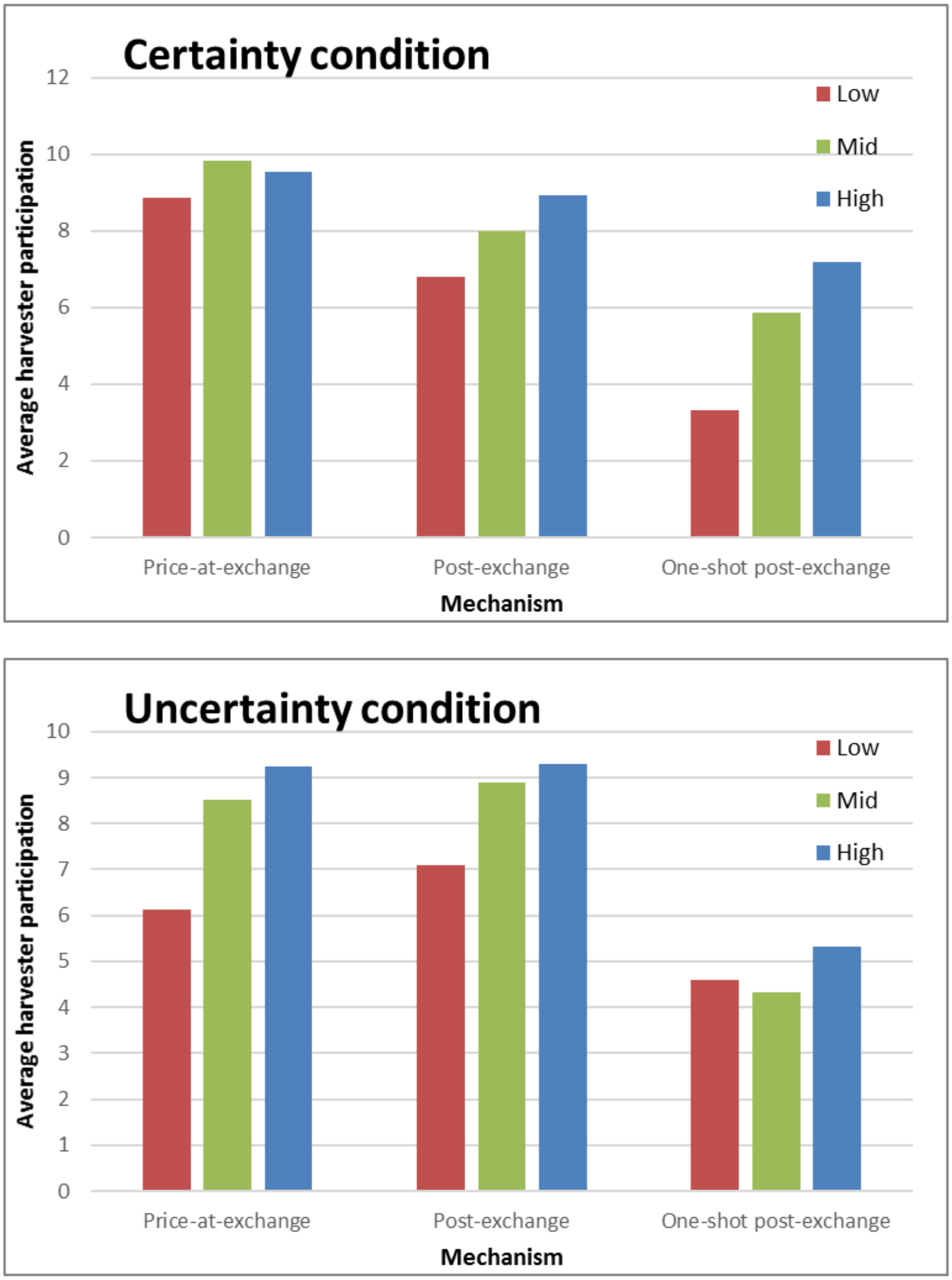

Figure 3.3. Average harvester participation per session by mechanisms and forecast levels under two conditions

Even though coefficients we obtain under REM is similar to OLS, rejecting the null hypothesis for Breusch and Pagan Lagrangian multiplier test for random effects (LM test) does suggest that we need to account for individual person pricing pattern that is unobservable to us. We also know that average ex-vessel prices vary across sessions. To control for cross session variation, we run a REM including session fixed effect (regression #3). REM with session fixed effect supports *both* of our hypotheses that we set out to test. Processors are paying less (more) to harvesters under the price-at-exchange than the post-exchange pricing mechanism under the certainty (uncertainty) condition. The one-shot game post-exchange processors are paying the least across out of the three mechanisms.

To control for quantity supplied on the ex-vessel price, we include total number of harvesters who participated in the market each period (regression #4). Including total number of producers in the market yields similar results as regression #3 with better R-squared (from 0.397 to 0.426). Key results remain unchanged under regression #4. Under uncertainty, processors are willing to pay 1.35 dollars *less* under the price-at-exchange than repeated post-exchange pricing with p-value at less than 1%. Under certainty, processors are willing to pay 0.56 dollars more under the price-at-exchange than the repeated post-exchange pricing mechanism even though the coefficient is not significant. The repeated post-exchange buyers are paying on average 1.57 and 2.7 dollars more under certainty and uncertainty conditions in comparison to the one-shot post-exchange buyers with both coefficient significant with p value less than 1%. For every additional harvester that participates in the market, processors on pays an additional $0.27 and the coefficient is significant with p value less than 1%. Table 3.4 displays the regression results #1 - #4. Table 3.6 and Figure 3.4 and Figure 3.5 record the differences in average prices paid by processors between the repeated post-exchange and the price-at-exchange and between the repeated to the one-shot post-exchange.

Table 3.4. Regression analysis results with ex-vessel price as the dependent variable

VARIABLES	(1) Ex-vessel Price: OLS	(2) Ex-vessel Price: REM	(3) Ex-vessel Price: REM	(4) Ex-vessel Price: REM
Mid Forecast	0.912***	0.884***	0.874***	0.566***
	(0.177)	(0.163)	(0.146)	(0.159)
High Forecast	1.712***	1.747***	1.750***	1.279***
	(0.173)	(0.158)	(0.173)	(0.228)
Price-at-exchange = 1	2.250***	2.313***	0.566	0.564
	(0.223)	(0.363)	(0.471)	(0.442)
uncertainty	2.859***	2.747***	2.788***	2.677***
	(0.223)	(0.270)	(0.434)	(0.353)
(Price-at-exchange)* uncertainty	-2.406***	-2.322***	-2.374***	-1.910***
	(0.308)	(0.361)	(0.501)	(0.433)
One-shot post-exchange =1	-1.567***	-1.060**	-2.162***	-1.569**
	(0.281)	(0.446)	(0.770)	(0.696)
(one-shot post-exchange)* uncertainty	-1.243***	-1.419***	-1.428	-1.132
	(0.407)	(0.466)	(1.063)	(0.963)
Total harvesters				0.265***
				(0.0669)
Constant	4.203***	4.100***	5.349***	3.193***
	(0.191)	(0.277)	(0.449)	(0.686)
Session Fixed Effect	No	No	Yes	Yes
Observations	1,125	1,125	1,125	1,125
R-squared	0.334	0.332	0.397	0.426
Number of id		104	104	104

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

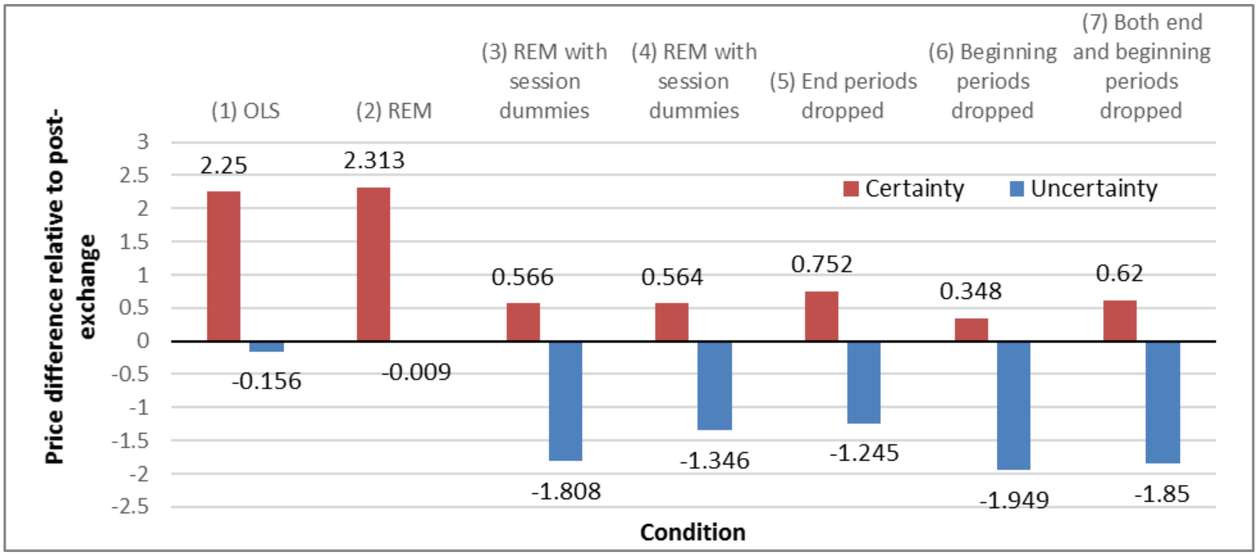

Figure 3.4. Average ex-vessel prices paid under the price-at-exchange relative to the post-exchange pricing under different regression methodologies

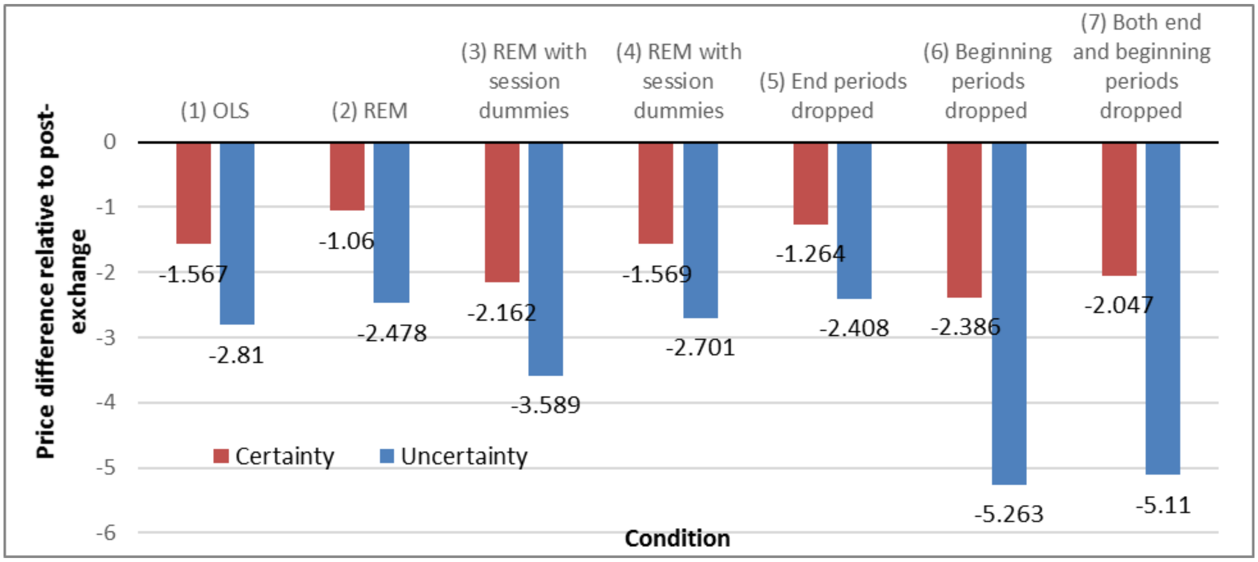

Figure 3.5. Average ex-vessel prices paid under the one-shot game relative to the repeated post-exchange pricing under different regression methodologies

To detect possible end-game effect, we drop observations from period 19 to period 25 using same set of parameters from regression #4. End-game effect would affect the post-exchange mechanism the most since processors may start behaving like the one-shot game post-exchange processors thereby influencing the ex-vessel prices. Regression #5 yields similar coefficient values as regression #4 with one exception where the average ex-vessel price paid by the price-at-exchange processors are higher than the post-exchange pricing processors under certainty with p-value at 8%.

In addition to the end-game effect, there is also the learning phase effect. Participants are likely be still learning how the game works during the first few periods of the game despite two practice rounds. It also takes a few periods before players reach an equilibrium state (Smith 1696). We drop observations before period 6 (regression #6) and again key results remain relatively the same with the exception on the coefficient of number of harvesters. Regression #6 suggests that processors are willing to pay an additional 11 cents to try to entice more harvesters to participate with p value at 8%. Furthermore, when we drop observations to account for both end-game and learning phase effects, the coefficient for number of harvesters drop to 9 cents with p value at 15% (regression #7). This suggests that once the game is at an equilibrium state, processors have no incentive to pay additional money to encourage harvesters from participating.

Even though the signs of coefficients remain consistent with the hypotheses we are testing, dropping the beginning periods under both regression 6 and 7 almost double the relative price differences paid between repeated and the one-shot game post-exchange pricing mechanisms. The price differences paid between the post-exchange and the price-at-exchange pricing mechanisms do not differ as much. This suggests possible learning by doing phase especially with the post-exchange pricing mechanism since this is not a method of transaction that is familiar to participants. Regression results and average ex-vessel paid between two mechanisms of 5 -7 can be found in Table 3.5 and Table 3.6. The coefficient value for number of harvesters participating can be found in Figure 3.6.

Table 3.5. Regression analysis results with ex-vessel price as the dependent variable with different periods dropped

	(5)	(6)	(7)
VARIABLES	Ex-vessel Price: period 19-25 dropped	Ex-vesesl Price: period 1-5 dropped	Ex-vesesl Price: period 1-5 and 9-25 dropped
Mid Forecast	0.600***	1.067***	1.156***
	(0.159)	(0.173)	(0.164)
High Forecast	1.328***	1.808***	1.951***
	(0.242)	(0.213)	(0.215)
Price-at-exchange = 1	0.752*	0.348	0.620
	(0.437)	(0.562)	(0.541)
Uncertainty	2.710***	2.797***	2.880***
	(0.352)	(0.447)	(0.455)
(Price-at-exchange)*uncertainty	-1.997***	-2.298***	-2.469***
	(0.427)	(0.529)	(0.535)
One-shot post-exchange = 1	-1.264*	-2.386**	-2.046**
	(0.722)	(0.936)	(0.975)
(One-shot post-exchange)*uncertainty	-1.143	-2.877**	-3.063**
	(0.994)	(1.192)	(1.235)
Total harvesters	0.260***	0.105*	0.0851
	(0.0710)	(0.0608)	(0.0599)
Constant	2.990***	4.479***	4.289***
	(0.722)	(0.727)	(0.723)
Session Fixed Effect	Yes	Yes	Yes
Observations	1,005	844	724
R-Squared	0.418	0.493	0.49
Number of id	104	87	87

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.6. Average ex-vessel prices paid under price-at-exchange and one-shot post-exchange pricing relative to the post-exchange pricing mechanism for each regression result

Average ex-vessel prices paid under the price-at-exchange relative to the post-exchange pricing				
Conditions\Models	(1) OLS	(2) REM	(3) REM with session dummies	(4) REM with session dummies
Certainty	2.250***	2.313***	0.566	0.564
(Std. Dev.)	(0.223)	(0.363)	(0.471)	(0.442)
Uncertainty	-0.156	-0.009	-1.808***	-1.346***
(Std. Dev.)	(0.213)	(0.362)	(0.434)	(0.416)

*** p<0.01, ** p<0.05, * p<0.1

Average ex-vessel prices paid under the one-shot relative to the repeated post-exchange pricing				
Conditions\Models	(1) OLS	(2) REM	(3) REM with session dummies	(4) REM with session dummies
Certainty	-1.567***	-1.060**	-2.162***	-1.569**
(Std. Dev.)	(0.281)	(0.446)	(0.770)	(0.696)
Uncertainty	-2.810***	-2.478***	-3.589***	-2.701***
(Std. Dev.)	(0.295)	(0.453)	(0.788)	(0.696)

*** p<0.01, ** p<0.05, * p<0.1

Average ex-vessel prices paid under the price-at-exchange relative to the post-exchange pricing			
Conditions\Models	(5) End periods dropped	(6) Beginning periods dropped	(7) Both end and beginning periods dropped
Certainty	0.752*	0.348	0.620
(Std. Dev.)	(0.437)	(0.562)	(0.541)
Uncertainty	-1.245***	-1.949***	-1.850***
(Std. Dev.)	(0.359)	(0.494)	(0.418)

*** p<0.01, ** p<0.05, * p<0.1

Average ex-vessel prices paid under the one-shot relative to the repeated post-exchange pricing			
Conditions\Models	(5) End periods dropped	(6) Beginning periods dropped	(7) Both end and beginning periods dropped
Certainty	-1.264*	-2.386**	-2.047**
(Std. Dev.)	(0.722)	(0.936)	(0.975)
Uncertainty	-2.408***	-5.263***	-5.110***
(Std. Dev.)	(0.683)	(0.952)	(0.930)

*** p<0.01, ** p<0.05, * p<0.1

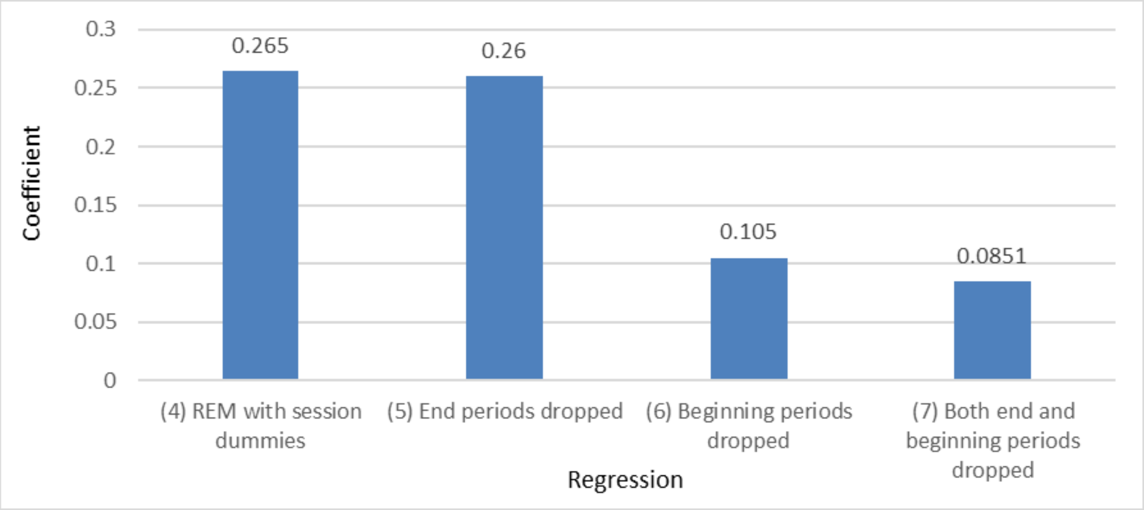

Figure 3.6. Coefficient value for number of harvesters participating under regression #4 to #7

3.4 DISCUSSION

The post-exchange pricing mechanism, in the case of Bristol Bay sockeye salmon fishery, has been thought as a mechanism reduces ex-vessel price since harvesters have forfeited their leverage. However, we argue that the post-exchange pricing creates a channel for risk-sharing between processors and harvesters when there are uncertainties in the market. We conduct controlled laboratory experiments treating the price-at-exchange mechanism as a benchmark. We find that without risks, processors are willing to pay $0.56 extra under the price-at-exchange than the post-exchange pricing mechanism. The price-at-exchange processors need to be competitive to secure catch share each period while the post-exchange processors are driven by the need to secure future catch shares. With a discounted value placed in the future, the post-exchange harvester receives less resulting in lower rents received.

With introduction of uncertainty in the wholesale market, processors are willing to pay $1.35 extra under the post-exchange pricing relative to the price-at-exchange mechanism. The price-at-exchange processors know that they need to endure the risks (for better or worse outcomes) are not willing to pay as much to harvesters up front. On the other hand, the post-exchange processors do not need to play the lottery and pay an implicit risk premium to harvesters through higher ex-vessel prices. The implicit risk premium not only covers the risk attitudes but also the discounted value difference between future and current catch share. This suggests that the post-exchange pricing mechanism in a market facing uncertainties can lead to better prices than the price-at-exchange mechanism.

The extreme case of the post-exchange pricing mechanism, where processors and harvesters only interact once, provides another benchmark for us to understand the role of securing future share of fish in such mechanism. The repeated post-exchange pricing processors are willing to pay \$1.57 and \$2.7 more under certainty and uncertainty conditions relative to the one-shot game post-exchange processors. The repeated post-exchange processors, knowing that harvesters can still switch to other processors next season, are offering ex-vessel prices similar to other processors to maintain catch shares in subsequent seasons. On the other hand, one-shot post-exchange processors do not have to worry about subsequent seasons since harvesters cannot distinguish processors from one season to another, resulting in lower ex-vessel prices.

Theoretically speaking, the one-shot game processors have no incentive to pay harvesters post-delivery. Harvesters, given that processors have no incentive to pay, would not produce in the first place. A possible explanation to what we observe in the experiment with positive ex-vessel price offers could be the free-rider problem in the initial stage of the game. Some processors in the game under the one-shot post-exchange pricing may try to encourage harvesters to sign up by offering positive ex-vessel prices even though harvesters cannot distinguish one processor from another in the next period. Other processors, knowing that harvesters cannot distinguish one processor from another in the next period, may take advantage of the processor who offers some positive ex-vessel price to get some harvesters to sign the contract and pays nothing. Harvesters, who learns throughout participating in the game, may refuse to sign up contracts at all or decide to gamble depending on the risk preferences. This explanation is supported by the fact that after we drop observations from period 1 to 5, the prices between one-shot and repeated post-exchange pricing mechanism almost doubled, from -\$1.56 dollars to -\$2.39 dollars under the certainty condition and from -\$2.7 dollars to -\$5.3 dollars under the uncertainty condition.

We test whether end-game and learning phase effects have any impact on the coefficient values that support our hypotheses. We find that dropping observations that may contribute to end-game and learning phase effects do not change our main conclusions. Total number of harvesters participating is the only exception. Learning phase effect seems to be the main driver in yielding positive significant coefficient value. In an equilibrium state, processors are happy with their choices and therefore have no incentive to decrease or increase their ex-vessel price offers to obtain higher current or future market shares. Harvesters are also satisfied with their decisions to either fish or not in an equilibrium state.

The experimental data has provided evidences that risk-sharing hypothesis better explains the post-exchange pricing mechanism observed in Bristol Bay. Since we have selected parameter value choices and cost structures based on Bristol Bay, it is unclear whether risk-sharing explains the post-exchange pricing mechanism in general. It would be interesting to test for factors in addition to future catch shares which sustains a post-exchange pricing induced risk-sharing mechanism. The theoretical models on the price-at-exchange pricing mechanism suggest that oligopoly or oligopsony pricing are sensitivity to capacity constraints and cost structures. Finding out critical values for the post-exchange pricing will rely on a rigorous theoretical model or more experimental data in the future.

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APPENDIX A: ADDITIONAL TABLES AND FIGURES FOR CHAPTER 1

Table A.1. Average age composition proportions used to allocate recruitment across age classes

Stock	1.2	1.3	2.2	2.3
Igushik	0.23	0.67	0.06	0.04
Wood	0.46	0.47	0.05	0.03
Nushagak	0.10	0.82	0.04	0.03
Kvichak	0.24	0.10	0.59	0.07
Alagnak	0.29	0.53	0.10	0.09
Naknek	0.18	0.44	0.18	0.19
Egegik	0.08	0.15	0.45	0.32
Ugashik	0.28	0.31	0.28	0.13

Table A.2. Matrix of harvest rate by fishing option and population ($h_{f,p}$) for the west side of Bristol Bay

Fishery Option	Igushik	Wood	Nushagak
Nushagak Section and Igushik Section	44%	60%	80%
Nushagak Section ONLY	20%	60%	80%
Igushik Section ONLY	30%	0%	0%
Wood River Special Harvest Area	0%	80%	0%
NONE	0%	0%	0%
Wood River Special Harvest Area and Igushik Section	30%	80%	0%

Table A.3. Matrix of harvest rate by fishing option and population ($h_{f,p}$) for the east side of Bristol Bay

Fishery Option	Kvichak	Alagnak	Naknek	Egegik	Ugashik
NONE	0.0%	0.0%	0.0%	0.0%	0.0%
Nak-Kvi District ONLY	50.0%	45.0%	50.0%	5.2%	2.0%
Egegik District ONLY	5.1%	3.7%	6.5%	95.0%	10.1%
Ugashik District ONLY	0.6%	0.6%	0.4%	3.4%	60.0%
Nak-Kvi AND Egegik Districts	52.5%	47.0%	53.3%	95.3%	11.9%
Nak-Kvi AND Ugashik Districts	50.3%	45.3%	50.2%	8.4%	60.8%
Egegik AND Ugashik Districts	5.7%	4.3%	6.9%	95.2%	64.0%
Nak-Kvi, Egegik, AND Ugashik Districts	52.9%	47.3%	53.4%	95.4%	64.8%
Naknek River SHA	0.0%	0.0%	90.0%	0.0%	0.0%

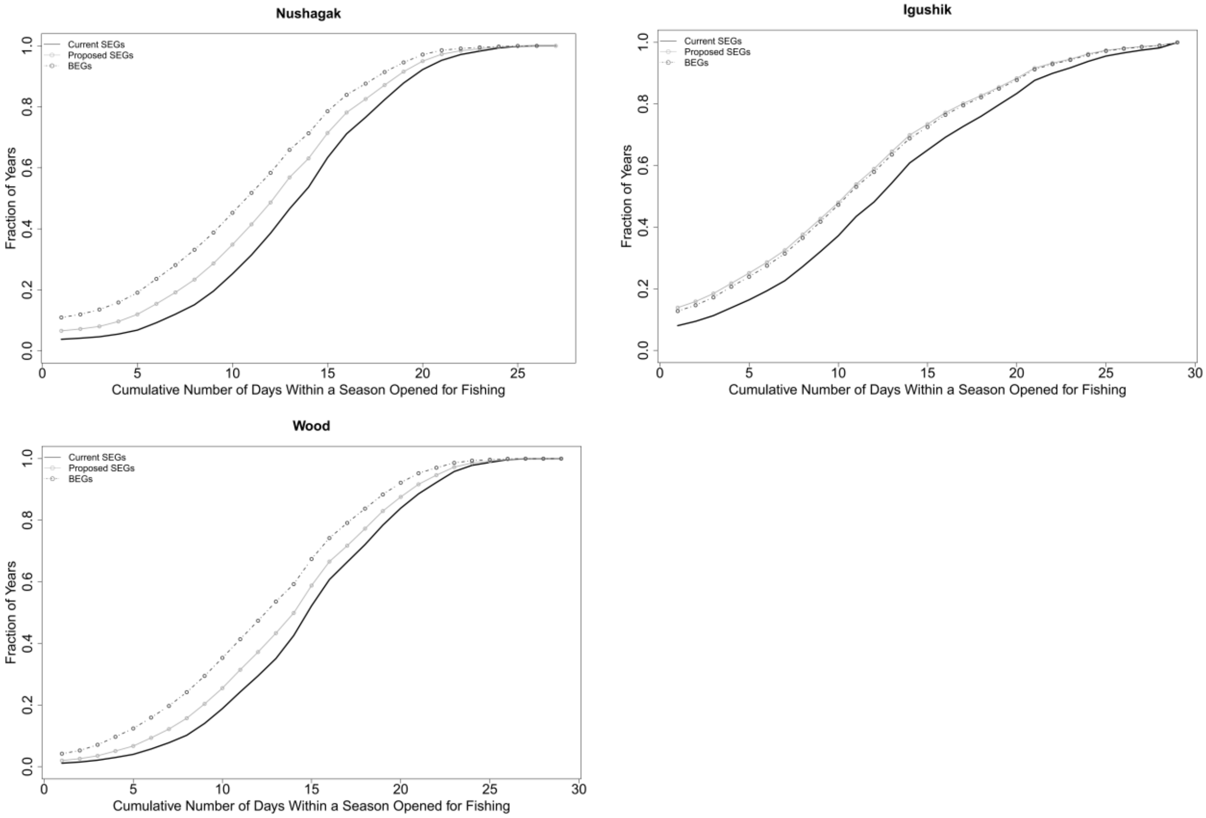

Figure A.1. Cumulative number of simulated years which a given sub-district was opened for a specified number of days during the period June 20th to July 17th

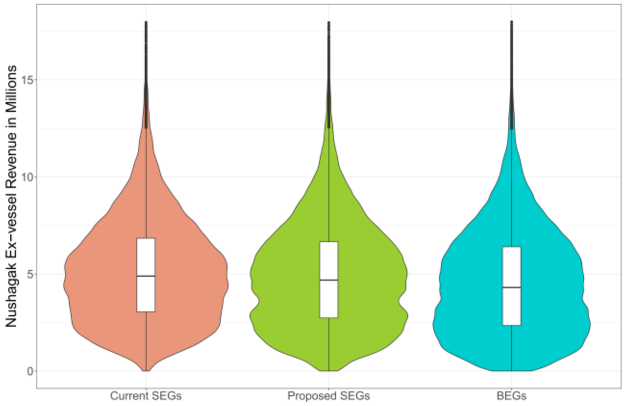

Figure A.2. Distributions of ex-vessel revenues from the Nushagak district under three escapement goal policies across 1,000 simulations of final 74 years each.

APPENDIX B: DATA SOUCES

1. Alaska Salmon Program Bristol Bay Preseason Forecast (UW-FRI)

Alaska Salmon Program publishes Bristol Bay preseason forecast every November. We use 2001 – 2012 preseason forecast data and the dataset can be found at: http://depts.washington.edu/aksalmon/

2. Alaska Department of Fish and Game (ADF&G) COAR data

ADF&G COAR data are available upon request from the Alaska Department of Fish and Game. For this project, we use annual ADF&G COAR data for statewide and Bristol Bay sockeye salmon production from 1980 – 2010.

3. Alaska Department of Fish and Game (ADF&G) Commercial Salmon Harvests and Ex-vessel values

ADF&G annual commercial salmon harvests and ex-vessel values can be found in the website below. We use annual data of Bristol Bay ex-vessel prices from 1994 – 2013 in this paper.

http://www.adfg.alaska.gov/index.cfm?adfg=CommercialByFisherySalmon.exvesselquery

4. Alaska Department of Labor and Workforce Development [Research and Analysis Section]

Alaska Department of Labor and Workforce Development provides Alaska census data, local employment by industry sector, and wages workers receive. We use 2001 – 2012 annual local employment by industry sector in the analysis. The data can be found at http://laborstats.alaska.gov/.

5. Alaska Department of Revenue Tax Division (ATR) data

ART trimester wholesale prices and quantity produced of fillet, H&G, and canned from 2002 - 2013 in Bristol Bay are used in this paper and can be obtained from the following website:

http://tax.alaska.gov/programs/programs/reports/index.aspx?60624

6. Department of Commerce, Community and Economic Development (DCCED) for State of Alaska

Office of Fisheries Development under DCCED for State of Alaska publishes recovery rate and yields from pacific fin fish and shell fish. The information can be found on the website below.

https://www.commerce.alaska.gov/web/ded/DEV/FisheriesDevelopment/SeafoodProcessingRecoveryRatesYields.aspx

7. Federal Reserve Bank of St. Louis Consumer Price Index (CPI) Data

The Federal Reserve Bank of St. Louis posts monthly CPI. The data can be found at:

https://fred.stlouisfed.org/series/CPIAUCSL

8. National Marine Fisheries Service (NMFS) Monthly Trade Data by Product, Country/Association

NMFS reports detailed data on U.S. imports, exports, and re-exports of salmon in the website below. We use monthly import and export quantities and prices from 1980 – 2012.

https://www.st.nmfs.noaa.gov/commercial-fisheries/index

9. Alaska Commercial Fisheries Entry Commission (CFEC) group level fish ticket landings data for Bristol Bay

CFEC maintains a confidential record of daily individual vessel landings data of Alaska fisheries since 1977. We obtain and use 2010 – 2012 daily landings data by group and district. Contact information with regards to CFEC can be found at: https://www.cfec.state.ak.us/index.htm

10. Alaska Department of Fish & Game (ADF&G) daily district registration data for Bristol Bay

ADF&G maintains a record of individual permit district registration data for Bristol Bay beginning of 2010 and are available upon request from ADF&G. For this project, we use 2010 – 2012 permit district registration data.

VITA

After completion of her degree, Yun-Ling Jocelyn Wang continues to work at T-Mobile as a Senior Technology and Economics Engineer. Her main research interests include experimental and behavioral economics, industrial organization, game theory and contract theory.