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Abstract

Risk Mitigation in the West Coast Commercial Fishing Fleet

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Physical and financial risk are inherently part of the commercial fishing industry. Working in rough seas for long hours with heavy equipment is notoriously hazardous and harvesters face some of the highest fatal and non-fatal occupational injury rates. Harvesters also face some of the highest financial risk across occupations as their income can vary greatly from demand shifts, stock variability, and regulations. In the following thesis, I examine how West Coast harvesters manage both physical and financial risk by utilizing data from two surveys of over 1400 U.S. West Coast fishing vessel owners. I explore what drives health insurance uptake by individual harvesters and how health insurance is used as a risk management tool. Health insurance uptake is found to primarily be driven by variables associated with health insurance cost rather than the benefit. Additionally, I find that health insurance coverage declined for West Coast commercial harvesters from 2017 to 2020. The drivers of individual responses to fishery closures are explored to understand different motivations and abilities to respond to closure driven financial risk. My results suggest that wealth drives individuals to avoid taking non-fishing work and community level economic health impacts an individual's ability to respond to a closure. Income diversification strategies of fishing different species or working outside of commercial fishing are found to be flexibly utilized when an individual faces a closure. Finally, I explore how income diversification as a risk mitigation strategy affects financial health as measured through credit scores. This work establishes a foundational understanding of West Coast fishery participants' relationship with credit health, finding that high credit scores are prevalent across the industry. I find that risk mitigation through income diversification is not clearly benefiting credit health, however, community level economic variables are significant drivers of credit scores. The results across my thesis chapters provide unique insights for managers looking to target harvester well-being through risk mitigation.

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Chapter 1

INTRODUCTION

1.1 Introduction and Overview

Throughout history and across the globe, commercial fishing has been consistently recognized as one of the riskiest professions (Schilling 1971; Thomas et al. 2001; Turner, Sainsbury, and Wheeler 2019). Working in rough seas for long hours with heavy equipment is notoriously hazardous (Janocha 2012), as fatal and non-fatal occupational injury rates for fishing are considered to be some of the highest across all industries (Labor Statistics 2011). Getting hurt can have compounding costs, leaving workers with expensive health care bills and lost wages as many harvesters lack paid-time-off (Crosson 2016). Occupational injuries, and a range of other long term health risks associated with heavy physical labor, have been found to have wide reaching consequences for harvesters, their families, and their communities (Woodhead et al. 2018).

In addition to the elevated physical health risks, commercial harvesters must also contend with wide swings in their interannual income as fisheries due to fluctuating abundance, prices and regulations (Kasperski and Holland 2013). In general, the more variable an individual or household's income is, the higher financial risk they face (Hardy 2017).

Improving both risk assessment and management is crucial given the high physical and financial risks associated with commercial fishing. As accessibility to large datasets, computer modeling and machine learning improve risk science (Aziz and Dowling 2018; Mannocci et al. 2021; Rawson, Brito, and Sabeur 2021), fisheries management has begun utilizing these tools to reduce human risk (Levin et al. 2013; Zador et al. 2017; Link 2018; Townsend et al. 2019; Pfeiffer, Petesch, and Vasan 2022). This thesis is a step in that direction as I explore three distinct risk mitigation techniques utilized by West Coast commercial harvesters: purchasing health insurance, fishing portfolio diversification, and the use of non-fishing work for income diversification.

Chapter 2, *Drivers of Health Insurance Status*, explores how West Coast Fisheries participants manage physical and financial risk by purchasing health insurance. Health insurance is a common tool used across the globe to manage and mitigate the risks associated with injuries and illnesses. Despite the increased risk of injury inherent in commercial fishing (Schilling 1971; Thomas et al. 2001; Turner, Sainsbury, and Wheeler 2019), little work examines the industry's relationship to health insurance markets with the exception of Crosson (2016).

Utilizing West Coast Fisheries Participation Survey data from 2017 and 2020 (Holland, Abbott, and Norman 2019), I build upon the methodology of Crosson (2016). While Crosson (2016) considered how differential risk across fishing activities might inform an individual's decision to purchase health insurance in North Carolina, I extend this consideration across the West Coast. I categorize the potential drivers for purchasing health insurance as variables corresponding to either the costs or the benefits of insurance. The magnitude and significance of the different factors are explored through a logistic regression model. Finally, I examine harvester health insurance coverage relative to county level health insurance coverage. The two survey years allow for a before and after comparison of the repeal and replace federal initiatives put in place to weaken the Affordable Care Act (Cohn 2020).

My research suggests that increased risk associated with fishing in dangerous weather conditions or gear type are not significant drivers of decisions to mitigate these risks with health insurance. However, I did find a relationship between target species and health insurance enrollment potentially related to differential risk mitigation. Individuals who participate in the notoriously dangerous Dungeness crab fishery were found to be more likely to have health insurance than individuals who fish for salmon. West Coast harvesters also experienced a more substantial decline in health care coverage than their county level communities following the repeal and replace federal initiatives of late 2017.

Chapter 3, entitled *Modeling Strategies to Cope with Fishery Closures*, explores the factors which drive how harvesters respond to the financial risks of fishery closures. These closures can drive income variability and financial hardships that individuals and communities face (Binkley 2000; Moore et al. 2020). One way to mitigate this risk is to diversify income sources by targeting multiple fish stocks or by taking work outside of the commercial fishing industry. However, the ability of fishing portfolio diversification and non-fishing income sources to allow harvesters to respond to fishery closures depends critically on whether these alternative income sources are available during the closure. Here, I examine whether past experience with these diversification strategies facilitates earning income during a closure. I also explore how age, household size and income, and community economic characteristics provide different motivations and abilities to respond to closures for the 2017 and 2020 West Coast Fisheries Participation Survey respondents (Holland, Abbott, and Norman 2019).

Through a multinomial logistic regression, Chapter 3 indicates that the higher a household income, the less likely a harvester is to seek work unrelated to commercial fishing in response to a closure. Previous experience with an income diversification strategy also was found to drive an individual to utilize the same strategy again. While not statistically significant, my model found that age and county level unemployment rate also guide fishery closure response strategies. Given increasing variability in fishing income in response to climate change (Peterson, Bond, and Robert 2016; Ritzman et al. 2018; "Summary for Policymakers" 2019), understanding response drivers can better inform management decisions and reduce the economic and social impacts of fishery closures.

In Chapter 4, *Does Risk Mitigation Improve Credit*, I explore the benefits of how risk reduction through income diversification strategies (explored in Chapter 3) influence the financial health of West Coast commercial harvesters. Credit scores are a strong indicator of financial health, as they are critical for accessing credit and are routinely used for "off-label" uses such as cell-phone contracts, access to rentals, and hiring decisions (Rona-Tas 2017). However, existing literature does not examine the relationship between credit scores and commercial fishing. In addition to exploring how income diversification might drive credit scores, I also establish a baseline assessment of West Coast harvester credit health.

Chapter 4 finds that West Coast harvesters, as a demographic, have excellent credit with average credit scores above the national average. This could indicate the importance that access to credit plays in determining who can enter the industry. Using an Ordinary Least Squares (OLS) model, I examine how past experience with diversification strategies, individual and household demographic variables, and community economic characteristics drive financial health as measured through an individual's credit score.

Of the limited demographic variables, only the highest category of household income significantly improved credit score. In contrast, the significance of community level economic variables suggests the importance of social nets for financial health. Another key result of Chapter 4 was the lack of significance in the estimated impact of fishing income diversification on credit scores. This suggests that income diversification within fishing does not necessarily reduce financial risk associated with credit ratings. In contrast, how evenly spread an individual's income was between commercial fishing and other industries was found to marginally improve credit score. This chapter provides a new approach for assessing income diversification in commercial fishing and suggests its effectiveness as a tool for risk mitigation is complex.

Chapter 2

DRIVERS OF HEALTH INSURANCE STATUS

2.1 Introduction

One of the most important ways to reduce risk is to properly understand and account for it. Since commercial fishing is commonly considered one of the riskiest occupations, there has been significant work exploring how West Coast harvesters mitigate financial risk related to income variability (Kasperski and Holland 2013; Richerson and Holland 2017). However, there is little published concerning how harvesters mitigate risk with health insurance (Crosson 2016). This is concerning given the evidence suggesting harvesters are under insured, have less favorable healthcare access, and are less likely to have a personal doctor compared with the general working population despite their high health risks (Turner, Szaboova, and Williams 2018; Speir et al. 2020).

Using data from NOAA and Washington Sea Grant's co-produced 2017 and NOAA's subsequent 2020 West Coast Fisheries Participation Surveys (Holland, Abbott, and Norman 2019), I aim to address this gap by comparing county level insurance rates of West Coast harvesters to the general population of their communities. Given the 2017 federal push to reduce the Affordable Care Act's scope, this study also provides insight into the effects of such policy changes on harvesters. Additionally, I explore what factors determine an individual's decision to purchase health insurance.

I categorize the potential drivers for purchasing health insurance as variables related to either the cost or the benefit of insurance. For purposes of this chapter, I consider both the implicit and explicit costs of health insurance while considering health insurance benefits as the reduced financial risk related to the likelihood of filing a claim and missing work. An individual at greater risk would therefore benefit from having health insurance more than an individual exposed to lower risks. I then estimate a series of logistic regression models to determine which factors significantly drive respondent's health insurance status across both survey years.

Of prior research on the fishing industry's relationship with the health insurance market, my work is most similar to that of Crosson (2016), who examined the relationship of the North Carolina commercial fishing fleet and private market health insurance purchases two years prior to the Affordable Care Act of 2010. Crosson (2016) found empirical evidence that harvesters were accounting for differential risk when deciding to purchase health insurance. Specifically, harvesters working off-shore who faced a much higher rate of injury due to fatigue were 40% more likely to have health insurance. Catch level values and capital investments as measures of the risk from higher levels fishing involvement were also found to be significant drivers of insurance uptake. The use of rod and reel, which was found to be associated with higher injury rates in North Carolina, was also a driver of health insurance. Crosson (2016) additionally found that being over the age of 65 as a dummy variable for being eligible for Medicare and household income were significant drivers. My models suggest that West Coast harvesters behave similarly, yet are potentially more driven by cost than benefits when determining whether to purchase health insurance.

Key findings are that harvesters were less insured in 2020 than in 2017 while also being less insured then their county level communities. While variables related to cost are clearly important drivers for the decision to purchase health insurance, benefit variables appear to have less of an effect. Addressing information gaps about differential risk in commercial fishing might be a productive way to address this potential mismatch. This study is unique in terms of its scale while providing insight for those who seek to create policies aimed at addressing fishing community health, well-being, and risk reduction.

2.2 Background

Shortly after the founding of the United States, the government recognized the importance of healthcare for American marine workers. In 1799, federal legislation was passed to subsidize medical care for maritime workers aboard U.S. registered or documented vessels, including fishing boats, through the Marine Hospital Service (Rao 2012; Randall and Grader 2020). In fact, this legislation was the groundwork for broader public health care in the United States, as the Marine Hospital Service was expanded and renamed the United States Public Health Service (PHS) in 1912 (Fee and Brown 2002). This legislation built a strong merchant and fishing fleet by mitigating the high financial burdens associated with the health risks of working at sea. Health was, and remains, a vital asset for harvester wellbeing and positively relates to fishing industry productivity more broadly (Speir et al. 2020).

Despite substantial improvements in reducing the risks associated with commercial fishing, occupational health hazards remain high [Jensen2014]. Long hours, rough seas, and working with heavy equipment create hazardous working environments. Falls on deck, machinery entanglement, and being struck by an object are common, increasing the likelihood of workplace injuries and deaths (Thomas et al. 2001; Janocha 2012). According to the Bureau of Labor Statistics (BLS), US commercial harvesters face fatality rates over 30 times higher than the average across all occupations (Labor Statistics 2011).

Nonfatal injuries and illnesses remain harder to quantify given the diversity and scope of commercial fishing and the difficulty of there being no single system in place for surveillance (Rautiainen 2021). Despite the difficulty in tracking, incidence rates of nonfatal occupational injuries and illnesses per 100 full-time workers is highest for individuals that work in agriculture, forestry, fishing and hunting collectively than any other professions as seen in Figure 2.1 (Labor

Statistics 2019). Of the 610 reported commercial fishing nonfatal injuries from 2003 to 2009, the two leading causes were overexertion and contact with equipment and objects (Janocha 2012).

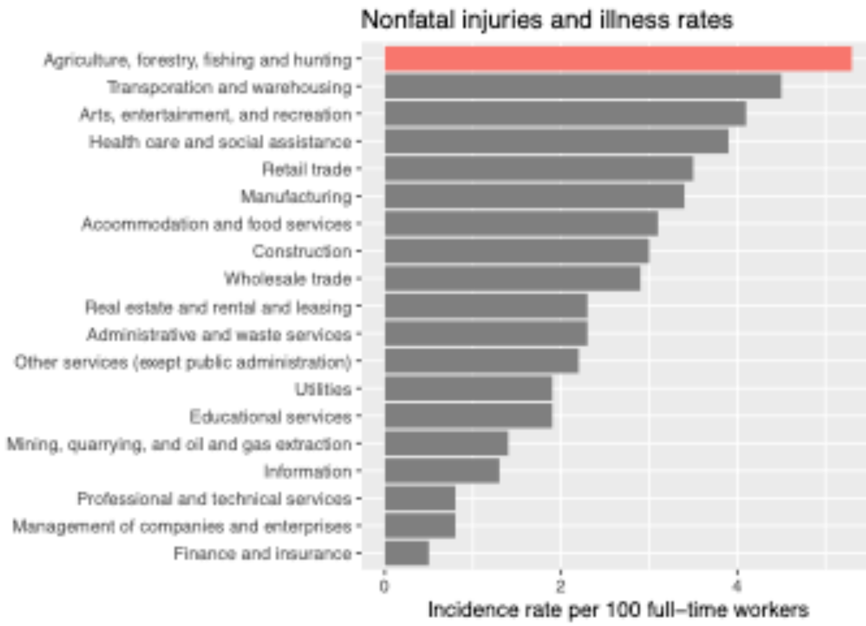

Figure 2.1: Incidence rates of nonfatal occupational injuries and illnesses by private industry sector, 2018. Data from [U.S. Bureau of Labor Statistics 2019.](https://www.bls.gov/iif/soii-charts-2018.pdf)

Injuries have compounding costs, leaving workers with expensive health care bills and lost wages. Unlike some other professions, an injury that restricts movement can fully prevent harvesters from being able to work given the physical demands of the fishing industry. The financial cost of missing work can be amplified given the short windows of some of the most lucrative fishing seasons. Occupational injuries may also result in difficult to quantify social costs, such as the downstream effect of a parent's workplace injury leading to emotional and behavioral impairment of their children (Asfaw et al. 2021).

In addition to physical accidents, harvesters are exposed to a range of other health risks associated with heavy physical labor (Woodhead et al. 2018). Full-time harvesters have been found to have higher rates of chronic musculo-skeletal problems than those who fished part-time (Lipscomb et al. 2004). Other work-related health risks include fatigue and exposure to environmental contaminants and noise (Silva et al. 2013). Risky, physical labor has been linked to detrimental lifestyle factors, such as excessive consumption of alcohol, smoking, and nutrient poor diets, and an increase in mental health issues such depression and anxiety amongst harvesters (King et al. 2015). In a survey of harvesters in Washington state, participants self-reported that they were somewhat more likely to limit their activities due to physical, mental, or emotional problems than those in other occupations (Speir et al. 2020). Similar to the impacts of physical injury, poor emotional and mental health have been found to negatively impact harvesters' families and communities reflecting the broad reach of these negative health impacts (Woodhead et al. 2018).

Regardless of the continued importance of healthcare for those who fish commercially, PHS Marine Hospitals were disbanded in 1980 as part of a general budget cut under the Reagan administration (Randall and Grader 2020; Fee and Brown 2002). As the fishing industry is largely composed of small family-owned businesses, the responsibility to source and purchase health insurance largely fell subject to the individual. This change drove harvesters to shift to rely on private health insurance markets, coverage from alternative jobs, Medicare, or choose to forego coverage. Since that time, the Affordable Care Act (ACA) was passed in 2010 with the goal of drastically increasing health insurance coverage across the US (Berchick, Hood, and Barnett 2018). While the ACA significantly increased insurance coverage rates from its inception through 2017, a change of administrations brought about policies aimed at weakening it (Patrick and Yang 2021). How the ACA and the policies aimed at reducing its strength have affected individuals who work in commercial fishing has remained largely unstudied.

2.3 Data and Methods

2.3.1 West Coast Fisheries Participation Surveys and Fish Ticket Data

In 2017, NOAA and Washington Sea Grant co-produced the West Coast Fisheries Participation Survey. In 2020, NOAA conducted a subsequent version. These surveys were mailed to all vessel owners with commercial fishery landings in Washington, Oregon, or California in the years directly prior to the surveys and were conducted using the Dillman (1978) approach, which included sending advanced postcards followed by the survey and a subsequent follow-up post card with another survey to those who had not returned the first. The surveys were designed to take approximately 20 minutes and a five dollar incentive was included in the first of the sent envelopes (Holland, Abbott, and Norman 2019).

A series of Pearson chi-squared tests were conducted by the survey designers, which found no evidence of response bias when considering the respondent characteristics of vessel length, horsepower, annual revenue, geographic area, or the number of individuals surveyed by 3-digit zip code (Holland, Abbott, and Norman 2019). The response rate for the surveys were over 50% with more than 1450 responses each year. The survey instrument tools and additional summary information is available online S1 LINK.

Figure 2.2: Number of survey respondents to the 2017 (a) and 2020 (b) West Coast Fisheries Participation Surveys by zip code. Zip codes with less than 10 respondents are not displayed.

In both 2017 and 2020, the vast majority of respondents were from the Washington, Oregon, and California, although there were responses from inland states as well as Alaska. For both survey years, the mean respondents' household income from fishing was 62%. The mean age for the two combined surveys was just under 58 years old and over 70% of the respondents had fished for over 20 years. While there were some differences in the questions asked between survey years, many remained the same.

Confidential vessel specific landing records (fish tickets) data was collected by state managers and archived in the PacFin database of the Pacific States Marine Fisheries Commission (PSMFC). After merging the survey and fish ticket datasets, variables related to potential differential risk drivers in commercial fishing were identified and constructed.

2.3.2 Small Area Health Insurance Estimate and County Level Data

To explore whether West Coast harvesters were under insured compared to the general population, I calculated the proportions of survey respondents with health insurance. For both years, only counties with more than 3 respondents were considered. Since the survey only collected spatial information regarding respondent zip codes, which do not line up one-to-one across counties and state lines, each respondent was assigned to one county. Individuals were assigned into the county with the highest ratio from the United States Department of Housing and Urban Developments cross walking database (Din and Wilson 2020). These ratios not only consider area, but also the distribution of businesses and populations across the zip codes. Thus, these counties had the highest likelihood of being that of the respondents.

County-level health insurance owning proportions were then compared with Small Area Health Insurance Estimates (SAHIE) from the U.S. Census Bureau. While survey county level health insurance proportions from 2017 were directly comparable, the 2020 SAHIE has not been provided yet, therefore the prior year estimates from 2019 were compared with 2020 survey proportions. Although direct comparison would be more ideal, I consider 2019 a reasonable comparison given that at the national level there was no change in the overall rate of health insurance coverage between early 2019 and early 2021 (Keisler-Starkey and Mykyta 2021).

2.3.3 Models of Health Insurance Status

To study what determines health insurance for West Coast harvesters, I estimated a series of logistic regressions where the dependent variable was a binary indicator variable of whether an individual had insurance or not. While demographic variables such as nativity, education, race, and gender have been found to be drivers of health insurance (Patrick and Yang 2021), I did not have access to this information and were therefore excluded from this analysis. These omissions are unlikely to create omitted variable biases as they are most likely not correlated with the model's dependent variables, which I classified as being related to either the cost or benefits of insurance.

Costs are important for health insurance uptake, with evidence that despite Affordable Care Act price reduction efforts, health insurance costs remain a major driver of gaps in coverage (Sommers 2020). Drawing from the survey questions, I identified three cost variables: household income, household size, and Medicare eligibility.

I posit if a household has a higher income, the cost of health insurance will be less of a burden and thus drive the purchase of coverage. Household income was categorically collected in the participation surveys by seven increments of 25,000 USD with one category capturing household income above 150,000. I reduced the variable to 4 categories of 50,000 USD increments to simplify model interpretation. Household size was also considered a cost variable positing that insurance through family plans might significantly help reduce premiums. To account for outliers, household size was reduced to 4 categories: single, two people, three people, or four or more people. The models also included a dummy variable to control for individual Medicare eligibility, the federal health insurance program for individuals 65 or older. This program dramatically reduces expenses related to health insurance and has been found to drive the decision for harvesters to have health insurance in other parts of the US (Crosson 2016).

Benefits are also important drivers of health insurance uptake. The benefit of having health insurance increases with an individual's likelihood of filing an insurance claim and its magnitude. This can also be summarized as risk, following the logic that RISK = PROBABILITY * CONSEQUENCE of Windle et al. (2008) which was used in a similar study on harvesters' health insurance in North Carolina by Crosson (2016). The greater the risk one faces, the greater the benefits of insurance. For example, I posit that age drives risk and therefore drives health insurance purchasing decisions, as older harvesters potentially take longer to recover compared to younger individuals who might be less risk averse (Steinberg et al. 2009).

To identify variables that might capture the benefits of having health insurance and given the difficulties of tracking nonfatal injuries, fatality data was used as a proxy for overall risk to inform how risk might differ across West Coast fisheries. In the US, deaths and safety incidents at sea are tracked and managed by the U.S. Coast Guard (USCG) while reports on such incidents are primarily generated by the National Institute for Occupational Safety and Health (NIOSH). NIOSH fatality data from 2015 through 2020 was compiled and divided by month, gear type and target species. Each of these variables appeared to display differential risk as captured through fatality distributions and were thus explored further in subsequent logistic regressions.

Weather is one of the most persistent risk factors that harvesters face (Jensen 2000; Jin and Thunberg 2005; Lambert et al. 2015; Finnis et al. 2019). Factors driven by weather such as wind speed and wave height can greatly increase the probability of accidents, which has led to policies to disincentivize fishing during risky weather (Pfeiffer and Gratz 2016; Pfeiffer, Petesch, and Vasan 2022). In fact, from 2000 to 2009, severe weather conditions contributed to 80% of fatal accidents on the West Coast (Lincoln and Lucas 2010). While severe weather can occur throughout the year, it is generally more common during the winter months. While fishing pressure might account for some of the fatality counts by months as shown in Figure 2.3 (a), a substantial number of fatalities did occur during the winter month of January. Therefore, fish ticket percentage of revenue by month was modeled to help control for differential fishing effort to explore if differential risk caused by when an individual fished helped determine the decision to purchase health insurance.

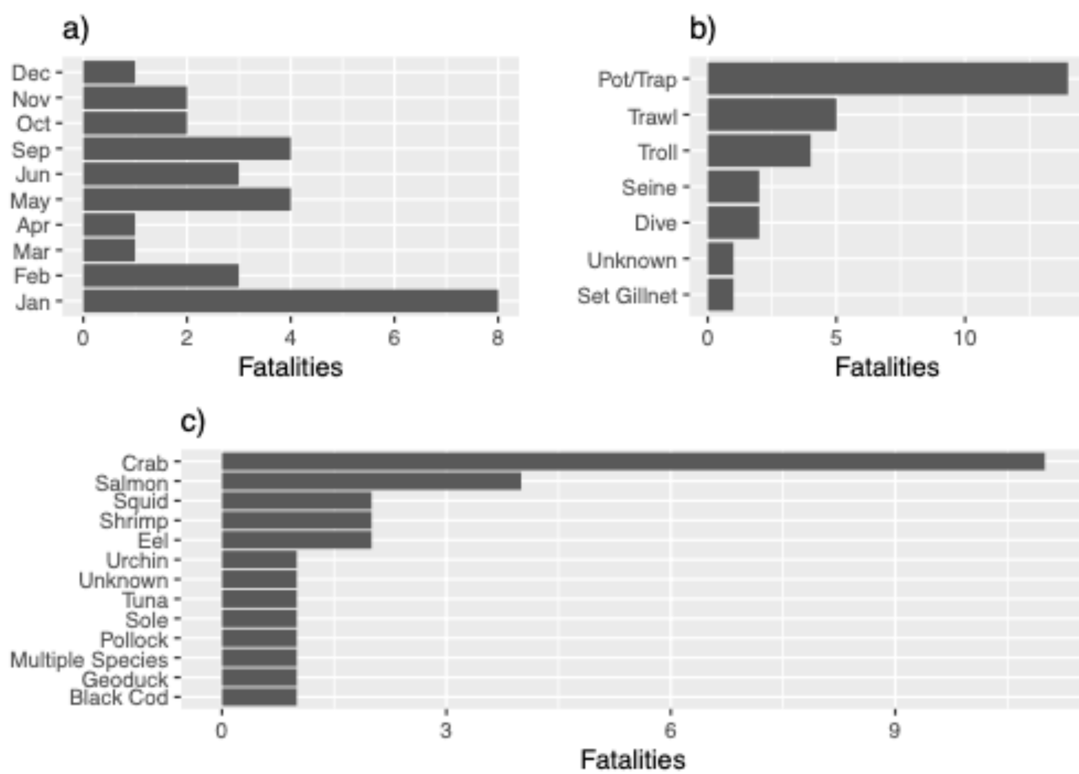

Figure 2.3: West Coast fatality counts by month (a), by gear type (b), and by target species (c) from 2015 to 2020.

Gear type is another variable that can affect risk in commercial fishing. Again, using the fish ticket data, dummy variables were created for whether revenue was reported from hook and line, pot, or trawl. While there is little work quantifying the different risks associated with gear types between West Coast fishing fleets, on the East Coast rod and reel was found to create the highest risk to injuries due to the repetitive motions and sharp hooks (Kucera et al. 2009). When using fatality count as a proxy for risk, it appears that pot and trap gear has the highest risk although this method does not account for differential use intensity and duration (Figure 2.3 (b)). Therefore, using fatality rates per 10,000 Full Time Equivalents (FTE) as calculated by NIOSH for the entire US commercial fishery from 2005 to 2014 gives a clearer picture of differential risk by gear type. As captured in Figure 5 of the report by Syron et al. (2015), the West Coast Multi-Species Groundfish Trawl had the highest fatality rate, just under 15 per 10,000 FTEs, of West Coast fleets followed by West Coast Non-Tribal Dungeness Crab with just over 10 per 10,000 FTEs. I posit West Coast harvesters mitigate this differential risk through health insurance and therefore individuals who use trawl followed by those who use pots and traps are more likely to purchase insurance given a potential greater benefit.

Target species were also included as a variable related to risk, creating dummy variables for whether an individual had revenue from salmon and another for whether they had revenue from Dungeness crab. Dungeness crab is largely believed to be one of the riskiest fisheries on the West Coast, making up most of the fatalities from 2015 to 2020 (Figure 2.3 (c)). In addition to the fatality count, the high fatality rate of just over 10 per 10,000 FTE for West Coast Non-Tribal Dungeness crab from 2005 to 2014 was considered to again account for differential effort. The Dungeness crab fleet's fatality rate was the 6th highest across the entire US commercial fishing industry and 2nd only to the Multi-Species Groundfish Trawl fleet on the West Coast (Syron et al. 2015). In contrast, West Coast salmon harvesters from the same period had a death rate well below a quarter of that of Dungeness crab harvesters (Syron et al. 2015). The commercial ocean troll salmon fishery typically runs from April through September while most Dungeness crab landings occur between December and February, which might also capture higher risk due to weather.

Fishing involvement has also been found to be a driver of health insurance as it increases the consequences of experiencing an injury (Crosson 2016). I identified two variables to capture fishing involvement: the percentage of household income from fishing to capture income dependence and individual Effective Shannon Index (ESI) capturing target species diversity. All regression models included household income from fishing, positing that the more one's livelihood depends on fishing, the higher the risk of getting hurt. Additionally, I posit that ESI captures fishing involvement, as the more species you target, the more gear and investments to gain access are required. Following this logic, the higher an individual's ESI, the higher their risk of injury given the physical requirements of fishing. In addition to fishing involvement, target species diversity also captures risk following the conjecture that the range of species a vessel targets might increase its overall risk due to differences in distances from a homeport and being less specialized (Kasperski and Holland 2013). Specifically, the mean Effective Shannon Index (ESI) for five years prior to the surveys was calculated from the fishticket data, following the equation where p_i is the proportion of individuals in each species:

$$ESI = exp(-\sum[(p_i) * ln(p_i)])$$

2.4 Results

2.4.1 County level comparison

To compare survey respondents to the general population of their communities at the county level, survey proportions of individuals with health insurance were compared to the SAHIE proportions. Only counties with more than 3 respondents were included to calculate proportions. For 2017, the mean proportion of survey respondents with insurance was .909 compared to the SAHIE proportions of the same counties of .921. The 2020 mean of surveyed respondent county proportions with health insurance was .8775 with the SAHIE mean for the same counties from 2019 with a mean of .916 (Table 2.1).

Table 2.1: Summary statistics for insurance percentages at the county level

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
County % insured (2017)	50	92.14	1.75	88.50	90.93	93.80	95.00
Respondent % insured (2017)	50	90.77	8.65	66.67	85.49	99.42	100.00
County % insured (2019)	53	91.73	1.84	88.00	90.30	93.10	95.10
Respondent % insured (2020)	53	87.75	10.74	50.00	81.25	95.24	100.00

While the county level SAHIE proportions' normality was confirmed using Shapiro-Wilk tests, the survey respondent proportions did not pass and were slightly negatively skewed, as seen in the normal quantile-quantile plots in Figure 2.4. Even with 50 observations for 2017 and 53 observations for 2020, there is an elevated chance for a type I error if conducting a paired t-test with the normality assumption violated. Regardless, conducting a paired t-test, there was no significant difference between respondents and their county level communities for 2017. However, respondents for the 2020 survey were statistically different with a lower proportion insured from their communities for 2019 ($p < 0.05$).

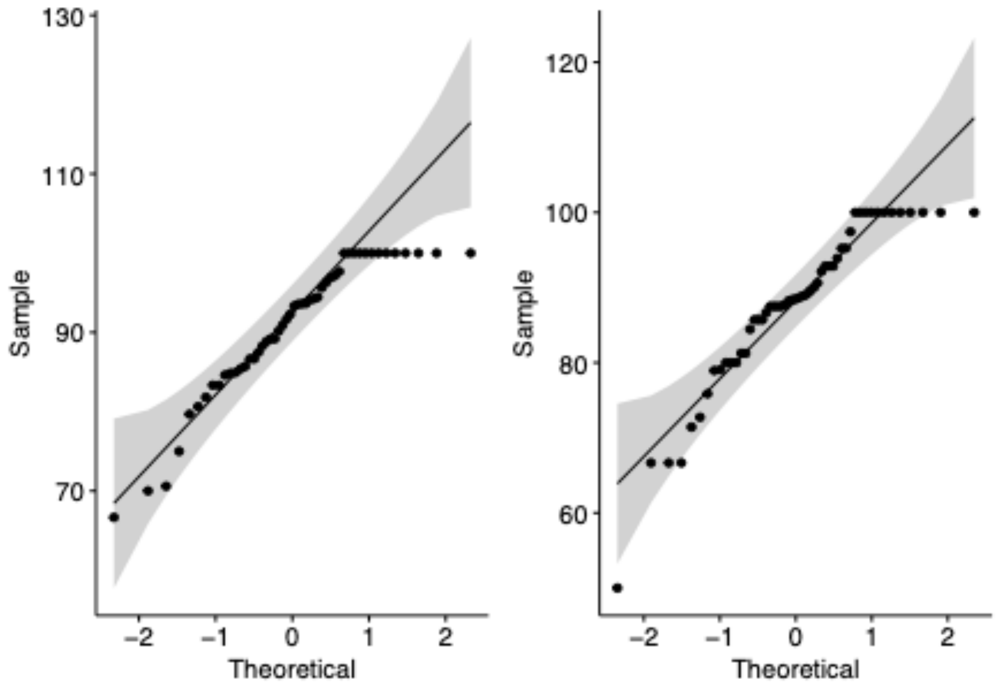

Figure 2.4: Normal Q-Q plot for survey respondent county level health insurance percentages for 2017 (left) and for 2020 (right).

To determine if the survey respondent and county level health care proportions are identical without assuming they follow the normal distribution, I also ran a Wilcoxon Signed-Rank test. The results of this test also found a significant difference with the 2020 respondents at the count level proportion estimates ($p < 0.05$) yet no significant difference for the 2017 proportions. Health insurance proportions for harvesters were also mapped for the two survey years (Figures 2.5).

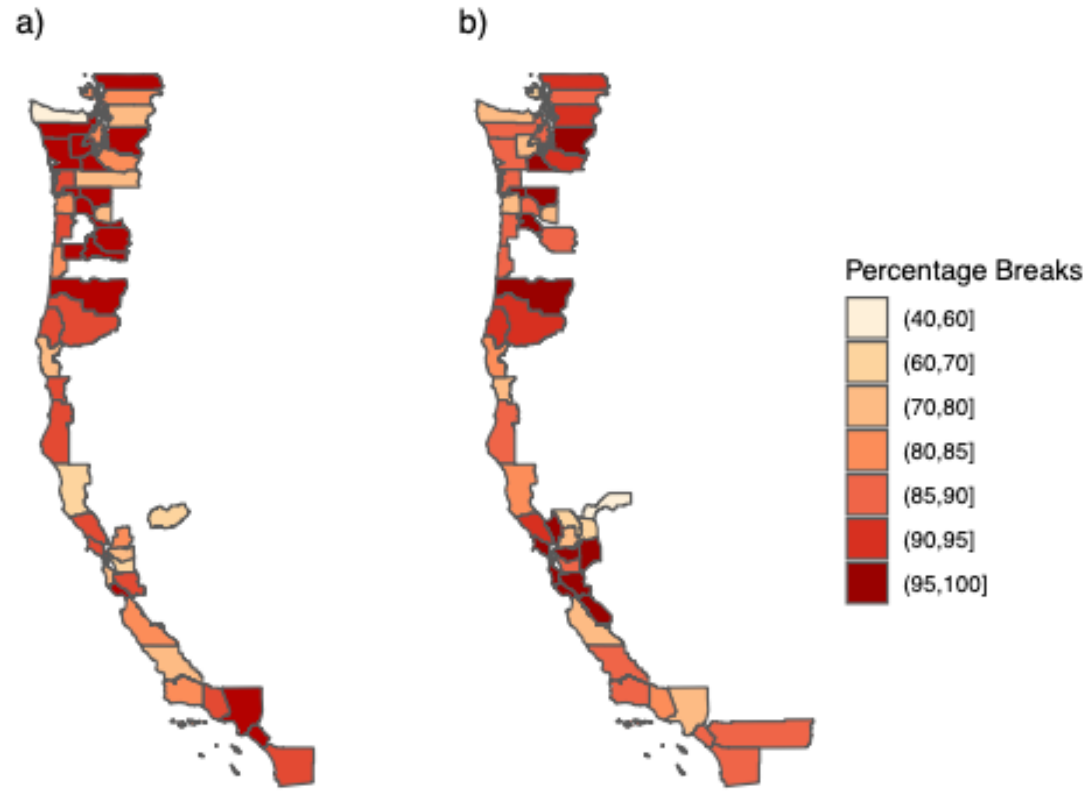

Figure 2.5: Percentage of survey respondents with health insurance at the county level for 2017 (a) and 2020 (b)

2.4.2 Model Construction and Evaluation

The initial logistic model of health insurance status contained all cost variables (dummy variable for Medicare eligibility, household size, and household income categories) and all benefit variables (age, percent of household income from fishing, mean ESI, dummy variables for Dungeness crab and salmon revenue, dummy variables for major gear type, and annual revenue percentage by month) along with state and survey year fixed effects.

The coefficients and standard deviations for the independent variables are provided in the first column of Table 2.2 capturing the coefficients and significance. The state fixed effects were not found to be significant and were not displayed in Table 2.2, although their inclusion or exclusion in the models is indicated. The first column captures the initial model followed by one without revenue by month and a final iteration without revenue by gear type. The models following the initial one no longer include state fixed effects.

Table 2.2: Primary logistic model determinants for the bianary variable of owning health insurance (1 = yes, 0 = no)

	Dependent variable:		
	Has Insurance		
	(1)	(2)	(3)
Over age 65	2.02*** (0.35)	2.02*** (0.35)	2.04*** (0.35)
Household of 2	0.19 (0.21)	0.17 (0.21)	0.19 (0.20)
Household of 3	0.69*** (0.27)	0.65** (0.26)	0.64** (0.26)
Household of 4 or more	0.64** (0.25)	0.62** (0.25)	0.62** (0.25)
Household income 50-100K	0.47*** (0.18)	0.48*** (0.18)	0.46*** (0.18)
Household income 100-150K	1.13*** (0.25)	1.13*** (0.24)	1.10*** (0.24)
Household income over 150K	1.94*** (0.35)	1.89*** (0.34)	1.87*** (0.34)
Age	0.03*** (0.01)	0.03*** (0.01)	0.03*** (0.01)
Percent of household income from fishing	−0.02*** (0.003)	−0.02*** (0.003)	−0.02*** (0.003)
Mean ESI for 5 years prior	0.35** (0.16)	0.35** (0.15)	0.30** (0.14)
Revenue from salmon (1 = yes, 0 = no)	−0.48** (0.20)	−0.48** (0.19)	−0.40** (0.17)
Revenue from Dungeness crab (1 = yes, 0 = no)	0.33 (0.30)	0.30 (0.22)	0.20 (0.17)
Proportion of annual revenue from Feb	−1.10 (0.96)	−1.15 (0.94)	
Proportion of annual revenue from Mar	0.48 (1.28)	0.45 (1.27)	
Proportion of annual revenue from Apr	1.45 (1.14)	1.32 (1.11)	
Proportion of annual revenue from May	−0.08 (0.64)	−0.12 (0.63)	
Proportion of annual revenue from Jun	0.51 (0.76)	0.48 (0.75)	
Proportion of annual revenue from Jul	−0.42 (0.65)	−0.50 (0.63)	
Proportion of annual revenue from Aug	0.73 (0.65)	0.68 (0.64)	
Proportion of annual revenue from Sep	0.69 (0.69)	0.56 (0.67)	
Proportion of annual revenue from Oct	0.17 (0.58)	0.14 (0.57)	
Proportion of annual revenue from Nov	−0.64 (0.80)	−0.66 (0.79)	
Proportion of annual revenue from Dec	0.71 (0.71)	0.77 (0.68)	
Revenue from hook and line (1 = yes, 0 = no)	−0.02 (0.19)		
Revenue from pot (1 = yes, 0 = no)	0.02 (0.29)		
Revenue from trawl (1 = yes, 0 = no)	−0.16 (0.58)		
Survey year (2020)	−0.22 (0.16)	−0.24 (0.16)	−0.30* (0.16)
Constant	0.20 (1.06)	0.09 (0.68)	0.34 (0.50)
State Fixed Effects	Yes	No	No
Psuedo R2	0.20426	0.20049	0.19133
Observations	2,231	2,231	2,231
Log Likelihood	−566.38	−569.06	−575.58
Akaike Inf. Crit.	1,212.76	1,188.12	1,179.16
Note:			*p<0.1; **p<0.05; ***p<0.01

The risk variables of gear type and of revenue proportion by month were not found to be significant in the initial model and were removed individually after confirming their removal reduced AIC (Bozdogan 1987). The likelihood ratio test between the full model in column 1 and the nested model in column 2 failed to prove that the models fit the data differently (p = 0.99), therefore the nested model is an improvement. Conducting a likelihood ratio test for model 2 and model 3, we again find that the models do not fit the data differently (p = 0.30). The changes to the coefficients were all relatively minor and the AIC was found to be the lower after removing state fixed effects as well. Keeping the survey year fixed effect lowered AIC despite not being significant and until the final iteration. While removing the non-significant dummy variable of revenue from Dungeness crab had the slightest decrease in AIC, it was kept following as it allows the comparison of a widely believed to be risky fishery with one that is not. Therefore, model 3 in Table 2.2 is my preferred specification.

2.4.3 Cost Variables

The dummy variable for if an individual was over 65 and therefore eligible for Medicare was significant across all iterations of the model ($p < 0.01$). This reduction in cost clearly drives the decision to purchase health insurance as was found when examining harvesters in North Carolina as well (Crosson 2016). A household size of 3 or 4 or more were also significant drivers of health insurance ($p < 0.01$). Across all iterations, household income had a significant positive relationship with the decision to purchase health insurance ($p < 0.01$). The strength of the relationship is captured with the increasing coefficients following the household income category, thus tracking with the ability of an individual to bear the costs of insurance.

2.4.4 Benefit Variables

Four of the variables posited as associated with benefits of insurance were significant across all iterations of the model. However, the significant ($p < 0.01$) negative value of the coefficient for percentage of household income from fishing was counter to what I posited and might instead be primarily capturing cost. Crosson (2016) used catch level value and capital investment as indicators of fishing involvement, theorizing that fishing involvement increased the consequences of injury due to lost earnings. I instead utilized the variable percentage of household income from fishing to capture risk associated with fishing involvement positing that it better captures dependence and risk. However, I found that the more a household's income came from fishing, the less likely an individual was to have health insurance ($p < 0.01$) despite higher risk from fishing involvement. Instead of capturing the benefits to counter increased risk, the negative coefficient of percentage of household income from fishing might primarily capture issues related to cost as households with other substantial sources of income could have access to lower cost healthcare plans available through external employers.

Three other variables that I posited as capturing the benefit of health insurance maintained significance across the model iterations. Age was found to significantly drive health insurance purchasing ($p < 0.01$), following the risk longer recovery times for older individuals (Gould et al. 2015). Second, the significantly positive relationship between health insurance and ESI ($p < 0.05$) might also be capturing the risk associated with diversifying within fishing, as there are associated dangers of having to work in unfamiliar areas and conditions in addition to the elevated risk of injury from higher levels of fishing involvement (Kasperski and Holland 2013; Crosson 2016). Third, the dummy variable for if an individual had revenue from salmon, a generally less risky fishery, was a statistically significant negative driver on health insurance ($p < 0.05$). This seems to suggest that individuals who have an increasing amount of dependence on salmon, might consider their fishing as less risky and are therefore less likely to acquire coverage.

The remaining benefit variables were not found as significant drivers of health insurance. None of the three dummy variables related to gear type were found to be significant and were removed for the following model iterations. This differs from the similar analysis by Crosson (2016) and might stem from the lack of definitive information for determining which gear type might be riskier on the West Coast (Syron et al. 2015; Lambert et al. 2015). Proportion of total revenue by month also was not found to be a significant driver of the decision to purchase health insurance and was removed following the second iteration, regardless of the potential increased risk of severe weather during the winter.

To check for multicollinearity between the predictors, I calculated the Variance Inflation Factor (VIF) for the full model. The VIF for all covariates in the estimation were less than 3.4, below the established cut off of 5, indicating an acceptable level of multicollinearity.

2.5 Discussion and Conclusions

By conducting both the paired t-tests and the Wilcoxon Signed-Rank tests with county level SAHIE proportions, I found that West Coast Participation Survey respondents were not significantly less insured than the general population in 2017 at the county level. However, respondents were less insured than the general populations of their counties in 2020. The survey respondents The paired t-test found that the 2020 survey respondents and their county SAHIE proportions from 2019 had a -3% mean of the differences. To help contextualize this difference, the Affordable Care Act (ACA), which is the most dramatic healthcare reform since the implementation of Medicare, was found to have increased the nationwide proportion of individuals with insurance from 2009 to 2015 by 7% [Patrick2021]. Thus, the 3% difference in insurance coverage between harvesters and their communities in 2020 is substantial. The significance of this difference can also be contextualized by comparing the 11.5% lack of health insurance coverage for harvesters in 2020 with the nationwide lack of coverage of 8.6% (Keisler-Starkey and Bunch 2021).

My county health insurance proportion comparison seems to capture ACA success since West Coast harvesters were not significantly less insured than their larger communities in 2017, despite being largely self-employed. The ACA largely achieved success by lowering coverage prices, taking advantage of the well-established price-elastic demand of health insurance in the US (Pendzialek, Simic, and Stock 2014), which decreased the number of people without health insurance by 13.3 million from late 2013 through 2017 (Berchick, Hood, and Barnett 2018).

Since 2017, the price of health insurance and uninsured rates have both increased across the US (Keisler-Starkey and Bunch 2020; Miller 2021). Policy changes brought about in 2017 through the repeal and replace platform challenged the ACA. While the goal to remove the ACA completely was unsuccessful, in late 2017 individual mandate penalties were repealed as part of the Tax Cuts and Jobs Act (Cohn 2020). Other federal actions at the time targeted removing key subsidies for insurers, reworking what private insurers could sell, and changing how states could design Medicare programs [LaFontaine2019; Cohn (2020)]. In 2018, the open enrollment period was reduced by 45 days and navigator program funding decreased by 84% with marketplace advertising being cut by 90% ("Obamacare: Has Trump Managed to Kill Off Affordable Care Act?" 2019). A Kaiser Family Foundation poll from November 2018 found that only 24% of

Americans knew the correct open enrollment deadline for 2019 (Kirzinger, Wu, and Brodie 2018).

The significant difference between the county level populations and respondents in 2020 could indicate that individuals in the fishing industry are reducing their health care coverage following the ACA decline. Additionally, the preferred iteration of my model also found a significant decline between the two survey years ($p < 0.05$). This is especially troubling considering the benefits that harvesters could gain from insurance given the elevated risks they face. Health insurance functions more than just to spread financial risks; it also supports the use of preventive and routine health care services that might otherwise be underutilized (Health Care Services 2003). These results are supported by the findings that fishing industry participants are covered by health insurance at lower rates than the general working population in Washington state (Speir et al. 2020), while also expanding the scope to the entire West Coast. Further research could help determine if this trend is occurring at a national level.

My work also offers insights into what drives the decision to purchase health insurance for West Coast harvesters. Across model iterations, I found evidence for the importance of cost for driving harvester insurance rates. The strongest determinant for health insurance was household income. Since the opportunity cost of purchasing insurance is less for households with higher incomes, insurance rates are higher. In this regard, fishing households can be assumed to follow the general findings that households with lower incomes are more likely to choose to avoid care and to be uninsured when faced with price increases (Griffith et al. 2020). This is further supported by the significant effect of being eligible for Medicare on West Coast harvesters having health insurance. Also, while household size dummy variables might be capturing some benefits of being insured as individuals with dependents might be more risk averse, it might be capturing cost as family plans usually reduce the price of coverage per individual.

In comparison to variables related to cost, variables related to the benefit of having health insurance as explained by risk were not all significant as drivers of West Coast harvester purchasing decisions. While I found evidence that differential risk between target species, age, and target species diversification was accounted for with health insurance, differences from the risk drivers of gear type and season were not found to be significant. This could stem from the difficulty of quantifying differential risk in general. If an individual is not fully aware of their risk, then they might be failing to properly mitigate it. More research and better communication of differential health risks might increase the utility of health insurance for harvesters as incomplete information has been tied to lower health insurance literacy, which has been associated with greater avoidance of both preventive and non-preventive services (Tipirneni et al. 2018).

In conclusion, while the 88.5% of West Coast harvesters with health insurance in 2020 might appear high at first glance, it is significantly lower than the county level averages. This is concerning considering the elevated health risks harvesters face. Since the viability of fishing communities requires sustainable levels of well-being and health (Speir et al. 2020), managers should consider ways to increase insurance uptake. While policies aimed at cost would likely have immediate impact, it is also important to address potential imperfect information issues regarding health insurance benefits for harvesters. Increasing health insurance coverage could help expand healthcare utilization and address how harvesters report poor general health and long-term illness rates that are among the worst of any occupational group (Turner, Sainsbury, and Wheeler 2019; Speir et al. 2020). Though this analysis focused on West Coast harvesters, it is likely that cost instead of benefit variables are primary drivers of health insurance uptake across the entire US commercial fishing industry. Ultimately, my hope is that these results can inform those who aim to address the well-being and health of commercial harvesters and their communities by mitigating risk with health insurance.

Chapter 3

MODELING STRATEGIES TO COPE WITH FISHERIES CLOSURES

3.1 Introduction

The saying that "fishing is not catching" captures its innate unpredictability. Despite the challenge of fishing's uncertainty, the adventure and accomplishment of overcoming difficulties draws many to prefer fishing over other higher paying jobs (Holland, Abbott, and Norman 2019). Yet in recent history, individuals in the commercial fishing industry have been facing unprecedented challenges as climate change and stock overexploitation have drastically increased the variability associated with how they make a living (Pershing et al. 2015; Oremus 2019). As managers respond to these impacts by implementing closures, harvesters and their communities have been cut off from substantial sources of income (Binkley 2000; Gien 2000; Jardine et al. 2020).

While research has provided insight on the effectiveness of different strategies to mitigate the financial risks of commercial fishing closures (Kasperski and Holland 2013; Anderson et al. 2017; Holland and Kasperski 2016), less is known about the underlying factors that drive how individuals respond. Responses can be categorized as either adapting or coping. An adaptive response is taking action that better positions an individual to endure through future shocks by altering livelihood patterns or building or altering an asset platform (Moore et al. 2020). In contrast, a coping response is a short-term action that enables an individual, household or community to survive a shock but requires a drawdown on some other form of capital, eroding the capacity to sustain through future shocks (Binkley 2000; Moore et al. 2020). In this chapter, I examine how past experience with diversification strategies, individual demographics, and community economic characteristics provide different motivations and abilities to respond to closures through either coping or adapting mechanisms.

The research developed in this chapter is motivated by the history of events that have occurred along the West Coast. Specifically, significant closures over the last 20 years have had widespread impacts on harvesters and their communities (Peterson, Bond, and Robert 2016;

Richerson and Holland 2017), which make it important to understand what drives financial risk mitigation strategies in the face of increasing income variability from climate driven closures.

While my analysis is focused on West Coast harvesters who experienced closures between 2018 and early 2020, there is the potential that similar factors drive closure responses across fisheries. Given the global trend of increasing variability in commercial fishing, understanding what drives closure responses will provide valuable insight to managers concerned with the impacts of fisheries management decisions on human well-being.

Through constructing a multinomial logistic regression, I find evidence that the higher a household income, the less likely a harvester is to seek work unrelated to commercial fishing in response to a closure. Another key finding is that previous experience with income diversification drives an individual to utilize the same strategy. While not statistically significant, my model also suggests the potential for age and county level unemployment rate to drive closure response strategies. Given the increasing impacts of climate change, understanding these influences might better inform management decisions to reduce the economic and social harm associated with fishery closures.

3.2 Background

Commercial harvesters contending with closures are part of a larger alarming trend in the United States of decreasing household financial stability, which is primarily measured through annual variation in income (Hardy 2017; Ha et al. 2020). While commercial fishing income variability has followed fish stock fluctuations throughout history, fishing income variability has increased following industrialization (Poulsen 2010; "Summary for Policymakers" 2019). Around the world, fish stocks have been declining as the result of overfishing and there is increasing recognition that managers must also account for climate-driven fish population changes in patterns and productivity at regional and global scales (Poulsen 2010; Kasperski and Holland 2013; Pörtner et al. 2022).

In general, the more variable an individual or household's income is, the less economic security they have. Income variability increases financial risk as it limits an individual's ability to pay consistent expenses or make investments. As fishery closures drive income variability, they can break down long-term financial planning strategies and cause them to be replaced with short term coping mechanisms, like depleting savings or taking on debt [Binkley (2000); Moore2020]. This insecurity can have far reaching economic and social consequences. In fact, income variability has been found to negatively impact the health of individuals and their families (Gien 2000; Hill 2021).

There are many recent examples of climate and overexploitation driven fishery closures with widespread economic impacts on the West Coast of the United States. For example, low returns of Coho salmon in the Sacramento River during 2008 and the collapsed fall-run of Chinook led to unprecedented closures and the declaration of a West Coast-wide federal disaster requiring 170 million USD in aid (Richerson and Holland 2017). In 2015, the West Coast Dungeness crab fishery faced closures following a marine heatwave and subsequent harmful algal bloom (HAB) that contributed to a 97.5 million USD decrease in revenue (Moore et al. 2020). Between 2014 and 2016, the Dungeness crab fishery also had to contend with major climate driven delays and closures due to shifting whale migration patterns and subsequent whale entanglements (Santora et al. 2020). Climate driven variations have also impacted West Coast pacific whiting, pink shrimp, and market squid fisheries (Peterson, Bond, and Robert 2016). There is evidence that climate change has driven harvesters to exit fishing with Oremus (2019) finding empirical evidence that fluctuations in a regional climate index reduced county-level fishing employment in New England between 1996 and 2017 by an average of 16 percent. These variations and closures could pose a similar threat to the West Coast fishing employment levels.

A common approach to reduce the financial risk from income variability is to diversify income sources. While originally introduced as a concept to manage risk in financial portfolios (Markowitz 1952), spreading income sources to limit exposure and reliance has been promoted in industries that depend on variable natural resources like fishing and farming (Costanza et al. 2000). One way income diversification can be achieved within commercial fishing is by targeting different species. While West Coast management practices have reduced fisheries access and generally decreased revenue diversification for fishing vessels over the last 30 year (Holland and Kasperski 2016), there is evidence that higher levels of diversification drive higher reduction of income variability (Kasperski and Holland 2013). The consistency of fisheries target diversity is also important, as large adjustments in diversification strategies from year to year have been found to be risky and increase revenue variability (Anderson et al. 2017). The strategy of income diversification for risk reduction can also extend to harvesters taking work in industries unrelated to commercial fishing. During closures, non-fishing work can provide an alternative income source until fishing is again possible.

Of the 2017 West Coast Fisheries Participation survey respondents who indicated that they were impacted by a fishery closure, 39% were impacted by some sort of closure involving salmon, while 28% were impacted by a closure involving crab. These two species alone accounted for 67% of the responses, reflecting their large share of participation in addition to their closures' impacts. In comparison, 35% of the 2020 survey respondents indicated they experienced closures associated with salmon and 31% experienced closures associated with crab. It is noteworthy that the 2020 survey was at the beginning of a global COVID-19 pandemic, which largely drove disruptions in export markets, the loss of restaurant sales, and the decline of seafood prices (Smith et al. 2020). However, of the 2020 survey responses, only 3% mentioned COVID-19 as a closure that disrupted their fishing. The utilization of the different strategies for responses to both survey years were plotted in Figure 3.1.

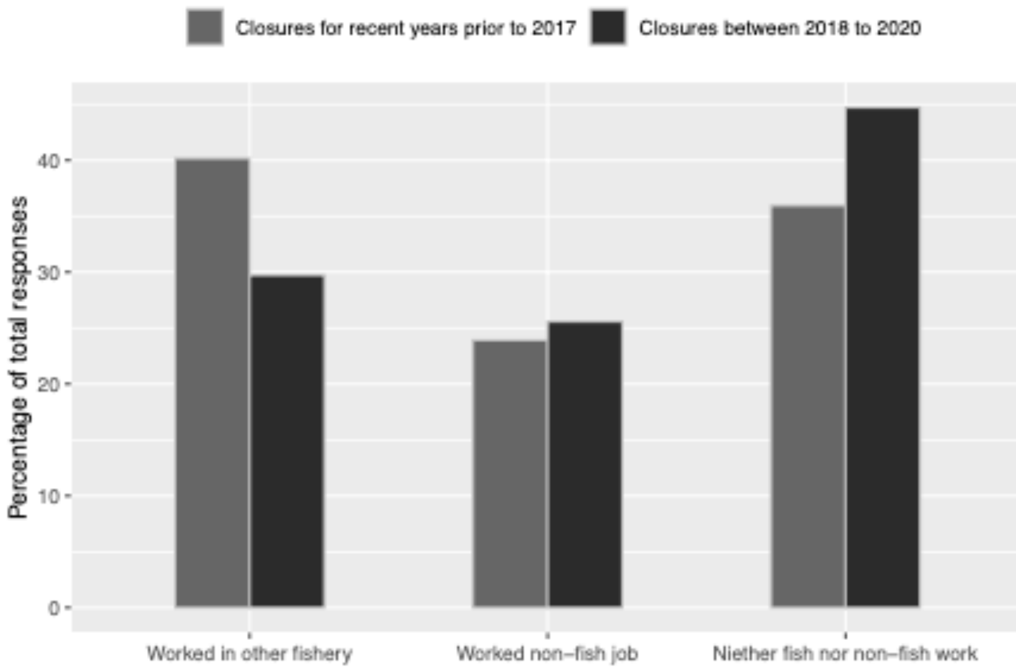

Figure 3.1: Percentage of West Coast Participation Survey respondents affected by closures utilizing each fishery closure response strategy for the 2017 survey, asking about recent year closures and the 2020 survey, asking about the last two years' closures.

In what follows, I explore how long-term income diversification strategies, demographic variables, community level economic health, and consecutive closures affect an individual's response to fishery closures utilizing a multinomial logistic regression analysis.

3.3 Data and Methods

As in Chapter 2, this study primarily relied on data from the 2017 and 2020 West Coast Fisheries Participation Survey responses with assigned counties. In 2017 the survey asked whether respondents had been affected by closures during the last few years while the 2020 survey asked about the last two years. These were question 14 and question 15 from 2017 and 2020 respectively. In 2017, 72% of respondents were affected by a closure while in 2020, 63% of respondents were affected. The high percentage of respondents from both years affected by closures is most likely influenced by the multiple year time frame they were asked to consider. Some respondents for the 2017 survey indicated they were considering closures within the last 10 years as recent. County level proportions of individuals impacted by closures for 2017 and 2020 are displayed in Figure 3.2, which only displays counties with 3 or more respondents. The higher proportion of individuals impacted by closures for the 2017 survey aligns with the coast wide HAB closures.

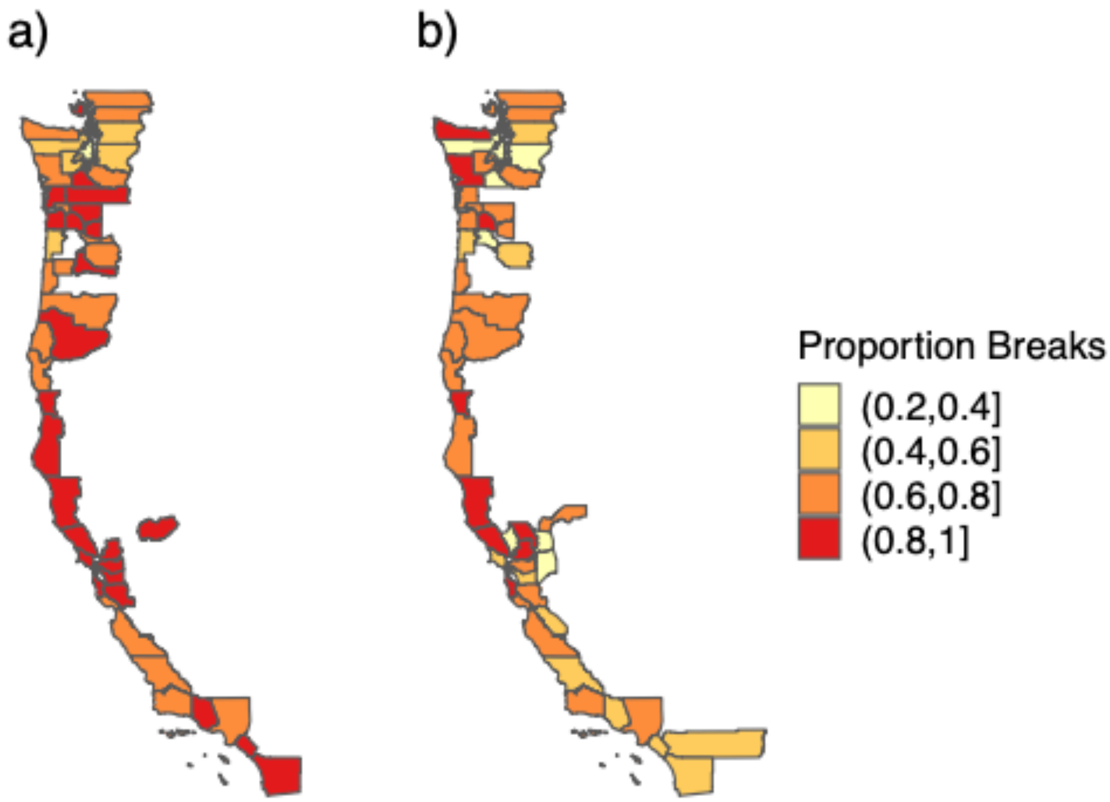

Figure 3.2: Proportion of respondents from 2017 (a) and 2020 (b) with fishing operations affected by fishery closures in the last couple years at the county level. Note: only displaying counties with more than 3 respondents.

On the survey instruments, the questions asking whether an individual had been affected by a closure were followed by questions that asked the respondents to indicate how they responded. The possible answers were "fished in another fishery" (f), "worked in a job or business other than commercial fishing" (w), or "did not work in either fishery or non-fishery employment during the closure" (n). While "fished in another fishery" and "worked in a job or business other than commercial fishing" are more likely adaptive responses compared with the coping response of "did not work in either fishery or non-fishery employment during the closure," they do not necessary imply taking action that better positions an individual to endure through future shocks. Hence, no distinction is made in this analysis. For both survey years, less than 10 respondents answered with both "fished in another fishery" and "worked in a job or business other than commercial fishing," so those answers were not included in my analysis given the difficulties in modeling such a disproportionately small group. Therefore, there are three discrete response choice decisions designated U_f, U_w, and U_n. The payouts of those options are captured in the following equation:

$$U_{nj} = \beta' x_{nj} + \epsilon_{nj}$$

Subscript j denotes the choice and subscript n denotes the individual. ϵ_{nj} is the difference between the utility that the decision maker actually obtains, U_{nj} , and the representation of utility developed using observed variables, βx_{ni}. The vector x_{nj} consists of the observed variables relating to alternative j. This consists of demographic, community, and income diversification variables that are defined in detail in the following paragraphs. To estimate the differences in parameters β as log odds from the U_w baseline, I constructed a multinomial logistic regression using the mlogit R package with the "worked in a job or business other than commercial fishing" response as the reference level (Croissant 2020). Assuming the errors are type 1 and follow an extreme value I distribution, the model implies the probabilities of choosing each of the other responses to the baseline are where i is the alternative choice:

$$P_{ni} = \frac{e^{\beta x_{ni}}}{1 + \sum_j e^{\beta x_{nj}}}$$

To explore factors that inform fishery closure response decisions, my model included individual level demographic variables collected in the surveys. Age was included, positing that it captures both fishing experience as well as age bias difficulties for finding alternative work. I also constructed a dummy variable for if a respondent was over the age of 65, which is the national average age for claiming social security benefits (Administration 2019). I posited that an individual would be less likely to seek alternative work as a response strategy given access to retirement plans, pensions, and/or social security. Household size was also included, positing that having dependents or codependents could alter an individual's strategy due to higher costs of living and responsibilities.

Household income was included in my model as well, positing that higher earners' savings and investments could allow them to avoid the effort needed to further diversify their income. To avoid endogeneity between respondent household income and closure response decision, the 2020 survey respondents were paired with their responses from 2017. Household income from 2017 was then used to capture wealth. As described in Chapter 2, the surveys categorically collected household income by seven increments of 25,000 USD with one category capturing household income above 150,000 USD. This was reduced to 3 categories of 50,000 USD increments to simplify model interpretation.

In addition to demographic factors that might help determine response strategies, I also included whether an individual had prior experience with income diversification through fishing different fisheries or working non-fishing jobs. This required the use of vessel-specific landings records (fish tickets) to calculate vessel landings diversity (Chapter 2). Like in Chapter 2, I utilized Effective Shannon Index (ESI) for the five years prior to the 2020 survey considering both West Coast and Alaska fishing diversity.

As in Chapter 2, I utilized Effective Shannon Index (ESI) for the five years prior to the 2020 survey considering both West Coast and Alaska fishing diversity. By including revenue diversity measured as ESI from the prior 5 years, I intended to test whether being diversified offered the ability to switch target species in response to a closure. Since there are increasing access restrictions in many marine fisheries through both moratoriums and license reductions (Kasperski and Holland 2013), higher ESI might indicate a necessary level of prior access needed to diversify within fishing when faced with a closure. Revenue ESI also might capture if a respondent has already made expensive investments in other fisheries regarding equipment and time.

Similarly, I posit if an individual already has experience or household connections with alternative work outside of fishing, then taking non-fishing work will be an easier response strategy to implement. I included household percentage of income from non-fishing related sources to capture how much income a house was already drawing from work other than fishing. Like household income, the percentage of household income from non-fishing work was taken from the 2017 survey as well to avoid endogeneity.

A dummy variable for whether an individual had responded as being affected by a fishery closure in the years prior to the 2017 survey was also constructed. I posit that if an individual had previously been affected, then the strategy of "did not work in either fishery or non-fishery employment during the closure" would be less likely. Having already taken an economic blow, a consecutive closure's consequences might require more adaptive responses for acquiring alternative forms of income.

To control for potential differences in various economic and social policies, state fixed effects were included in the model. County level economic variables were also included, positing that an individual's response strategy could also be affected by their county level community's economic well-being. For example, individuals from a county with low unemployment and high Gross Domestic Product (GDP) may have more opportunity to respond to a closure by working in another industry while realizing greater benefits from this strategy. Including county level unemployment rates in my model was supported by the findings that unemployment rates increase the duration of individuals' job searches (Baumann 2016), thus potentially driving individuals away from the non-fishing work response strategy. County GDP was used as a proxy for the benefits of non-fishing employment, as a higher GDP might indicate a stronger overall economy at the community level. Therefore, both 2020 county-level unemployment and 2020 Gross Domestic Product (GDP) data was compiled from the BEA and included in the model.

While 673 of the 1461 2020 survey respondents were impacted by closures, only 290 were able to be matched with the 2017 survey data. Of the observations in the model, 30.21% responded "fished in another fishery," 21.52% responded "worked in a job or business other than commercial fishing," and 48.26% responded "did not work in either fishery or non-fishery employment during the closure." These percentages can be viewed in comparison with the unmatched 2020 survey responses in Table 3.1. For all the explanatory variables there was no evidence of multicollinearity after constructing a correlation matrix.

Table 3.1: Summary table for closure response percentages for matched and unmatched survey data

	Closure Response	Matched %	Unmatched %
1	Did not work in either fishery nor non-fishery employment during the closure	47.93	45.32
2	Fished in another fishery	30.34	28.23
3	Worked in a job or business other than commercial fishing	21.72	26.45

3.4 Results

3.4.1 Multinomial Logistic Closure Response Strategy Model

The coefficients of the independent variables measure the changes in the log odds of either "fished in another fishery" or "did not work in either fishery or non-fishery employment during the closure" relative to "worked in a job or business other than commercial fishing" (Table 3.2). The model was predictive of group classification, $X^2(26) = 64.56$, $p<.001$; McFadden $R^2 = .107$ and correctly classified 56.25% of the respondents' closure response strategies, noting that chance alone would correctly classify 33.33%. After testing the model, responding by neither fishing nor non-fishing work was correctly classified for 76.97% of the observations, responding with non-fishing work was correctly classified for 46.77% of the observations, and fishing in another fishery was classified correctly for 29.88% of the observations.

Table 3.2: Closure Response Strategy Multilogit Model

	Dependent variable:	
	Other Fishery	Did Not Work
	(1)	(2)
Age	0.01	0.04*
	(0.02)	(0.02)
Over 65 (1 = yes, 0 = no)	0.48	0.24
	(0.57)	(0.53)
Household size	0.14	−0.01
	(0.16)	(0.16)
Household income 50-100K (2017)	0.40	0.62
	(0.44)	(0.41)
Household income > 100K (2017)	0.99**	1.28***
	(0.47)	(0.44)
Mean ESI 2012-2016	1.06***	0.48
	(0.38)	(0.38)
Household non-fishing income percentage (2017)	−0.02***	−0.02***
	(0.01)	(0.01)
Consecutive closures (1 = yes, 0 = no)	−1.82	−0.85
	(1.13)	(1.15)
County level unemployment rate	0.25*	0.38***
	(0.15)	(0.14)
County level GDP (millions of USD)	−0.001	−0.003
	(0.002)	(0.002)
Constant	−2.48	−4.67**
	(2.26)	(2.24)
State Fixed Effects = Yes		
Observations = 290		
Log-Likelihood =-268.35		
McFadden R-Squared = 0.107		
Likelihood ratio test : chisq = 64.559 (p.value = 1.4126e-05)		
Note:		*p<0.1; **p<0.05; ***p<0.01

The results revealed that of the demographic variables, prior household income above 100,000 USD a year was a significant predictor of coping with "did not work in either fishery or non-fishery employment during the closure" ($p < 0.01$) and "fished in another fishery" ($p < 0.05$). Age was not found to be significant, but the model suggests that older harvesters might be more likely to neither fish in another fishery nor work a non-fishing job ($p < 0.1$). This would support the findings that older individuals have more difficulty finding new sources of employment (Baumann 2016). Both of the demographic variables household size and being over 65 are either unimportant as indicators for how one responds to closures or are imperfect measures that should be refined in future work.

A harvesters' prior experience with income diversification was a significant predictor of being able to respond to a closure by fishing in another fishery. Specifically, there was a positive and significant relationship between mean ESI from the past five years and the "fished in another fishery" response strategy ($p < 0.01$). Similarly, prior experience with non-fishing work as captured by 2017 household income percentage from non-fishing sources significantly drove individuals towards responding to a closure with non-fishing income ($p < 0.01$). Experiencing consecutive closures was not found to have a significant effect on response strategy, however, this is potentially due to there only being 16 respondents who had not experienced a closure in 2017 compared with 272 who had. A more even distribution might improve future models examining consecutive impacts.

The results from the model also suggest that large scale community socioeconomic variables drive individuals' decisions to respond to fishery closures. As unemployment of a respondent's community increased, there was significantly a greater chance that an individual responded to a closure by not working in either fishery or non-fishery employment during the closure ($p < 0.01$). Additionally, as unemployment of a respondent's community increased, a respondent was more likely to respond to a closure by fishing in another fishery ($p < 0.1$). County GDP and state fixed effects were not found to be significant in this model, again suggesting that they are either unimportant indicators of how an individual responds to a closure or are potentially limited by observation count and effect size.

3.4.2 Hausman and McFadden Tests

Multinomial logistic regression assumes independence of irrelevant alternatives, stating any item added to the set of choices will decrease all other items' likelihood by an equal fraction (Benson, Kumar, and Tomkins 2016). To check that this assumption holds for my model, I constructed 3 logistic models with the different groupings of the closure response choices and compared them to the primary multinomial logistic model using Hausman and McFadden tests. Across all restricted model tests, the independence of irrelevant alternatives assumption held.

3.5 Discussion and Conclusion

Fishery closures affected over 60% of West Coast Fisheries Participation Survey respondents for both survey years. This is particularly concerning given not only the negative impacts on the harvesters themselves, but also to their extended communities (Ritzman et al. 2018; Moore et al. 2020). While the current data does not allow for a comprehensive comparison of response strategies over time, the percentage of harvesters responding to closures by fishing in other fisheries decreased from 2017 to 2020, while the percentage of harvesters coping by neither fishing or taking non-fishing work increased. One potential driver of this shift could be the COVID-19 relief program, which was occurring during the 2020 survey. This might have led harvesters to the "did not work in either fishery or non-fishery employment during the closure" strategy given increased monetary assistance for individuals out of work. The ambiguity in defining "recent years" also makes comparisons difficult, as the longer-term considerations of respondents in the 2017 survey might account for the higher percentage of the adapting behavior of "fishing in another fishery." Continuation of this survey work will help determine if there is a longer-term directional change in response behavior.

The multinomial logistic regression modeling of the three different fishery closure response strategies for US West Coast harvesters provided insights into drivers of individual closure responses. The results indicate that individual income and past utilization of income diversification strategies are significant drivers of response strategy selection. Prior income above 100,000 USD significantly drove harvesters away from responding with non-fishing work, possibly reflecting the high preference and social capital harvesters place on fishing over other sources of income (Holland, Abbott, and Norman 2019). These results are empirical evidence that making the decision to continue fishing or wait out the closure is resource dependent.

How diversified an individual's income was within commercial fishing, as measured through mean ESI, was found to significantly drive the "fished in another fishery" response strategy. These results agree with the conclusions of Richerson and Holland (2017), which found vessels that exited fishing following a West Coast salmon closure tended to be less diversified, indicating that these types of vessels may be less resilient to a closure or decline in target species availability. The same study found that while diversification was positively associated with being active in fishing during the closure, there was only limited evidence that these vessels increased their participation in other fisheries (Richerson and Holland 2017).

Additionally, capturing the complexity of fishing income diversification, high year-to-year variations in fishing diversity has been found to increase income variability and financial risk (Anderson et al. 2017). While fishing income diversity might allow an individual to continue fishing in the short term, future work is needed to determine if these decisions are profitable long term. If fishing in another fishery was an experimental adaptation strategy for respondents in 2017, its potential lack of viability as a response could be reflected in the 2020 shift to harvesters coping by responding "did not work in either fishery or non-fishery employment during the closure." Further monitoring and research is needed to determine if this is a general trend that holds across the West Coast. It is also important to note the different time frames considered between surveys limit the ability to make direct comparisons.

Prior percentage of household income from non-fishing work was also found to be significant as a predictor of responding to a closure with non-fishing employment. This supports the conjecture that small independent owner–operators might already have non-fishing income as an established strategy to mitigate income variation, allowing them to cease fishing when conditions are poor, and/ or to supplement their fishing income during bad years (Richerson and Holland 2017). My findings suggest individuals without prior experience in their households with non-fishing work might be limited in their closure response options.

Despite not being statistically significant, potentially due to a limited number of observations, variables on the margin ($p < 0.1$) provide further insight into both individual and community level drivers of closure response strategy selection. The negative relationship of unemployment rate and the strategy of "fished in another fishery" suggests community level variables can provide insight for individual response choices. Additionally, county level unemployment was a significant driver of the "did not work in either fishery or non-fishery employment during the closure" response ($p < 0.01$). My findings support how the common policy goal of reducing unemployment (Chakraborty et al. 2020) would benefit commercial harvesters adapting to closures. These results, in consideration with the prior household experience driving non-fishing responses to fishery closures, could help in identifying variable vulnerability across fishing communities to closures.

Age was found to be a marginal driver of the "did not work in either fishery or non-fishery employment during the closure" response. Yet, future research with larger samples will be required to determine if there is a significant effect of age on response strategies, potentially stemming from age bias against hiring older individuals in alternative jobs. My model also did not find a significant effect for if an individual was over 65 and therefore at the average benefit claiming age for social security (Administration 2019). This might indicate that social security is not viewed as a significant safety net to allow for harvesters to cope with closures.

As oceanic conditions continue to vary as the result of climate change, consecutive impacts of closures will most likely increase in occurrence (Ritzman et al. 2018; "Summary for Policymakers" 2019). In this case, coping will likely become less viable as a response and force adaptations or exits from fishing altogether. The longer harvesters cope with closures, the more financial risk they face as long-term unemployment has been found to have broad consequences such as driving an individual to earn less once taking a new job while also potentially lowering personal and familial health (Nichols, Mitchell, and Linder 2013). Managers concerned with the well-being of harvesters and their communities must continue to monitor response decisions from the lens of risk science. Further understanding the drivers of closure response will be critical for guiding policies to effectively mitigate consequences of fishery closures.

Chapter 4

DOES RISK MITIGATION IMPROVE CREDIT?

4.1 Introduction

As introduced in the previous chapters, commercial harvesters face both heightened physical and financial risk (Chapter 2; Chapter 3). Chapter 2 found evidence that West Coast harvesters have less health insurance and a higher risk of occupational injury than the general public. Chapter 3 found that the past use of an income diversification strategy drives an individual to use the same strategy when faced with the financial risks of fisheries closures (Chapter 2). In this final chapter, I estimate a series of Ordinary Least Squares (OLS) models to examine how utilization of income diversification strategies, individual demographics, and community economic characteristics drive West Coast harvesters' credit scores as a proxy for financial health. Like the previous chapters, this chapter again utilizes the West Coast Fisheries Participation Survey data (Holland, Abbott, and Norman 2019).

Since the 1950s, consumer lending in the United States has largely been centered on credit scores and reports (Giorgi, Harding, and Vasconcelos 2021). Access to credit is now a critical way individuals and their families can improve living standards by gaining the ability to invest in education, housing, or personal business ventures while also providing a cushion to financial shocks from medical emergencies or lost income (Hartley, Mazumder, and Rajan 2019). While credit scores, which are 3-digit estimates of how likely a borrower is to repay debts, are meant to inform access to credit, they are increasingly subject to "off-label" use, which is use beyond the original intention (Rona-Tas 2017). This "off-label" use of credit ratings across society has been attributed to the growing role of finance in modern life (Deutschmann 2011). For example, credit scores are routinely used in fields such as auto insurance assessments, cell phone contracts, residential rentals and even hiring decisions (Rona-Tas 2017). Credit scores have been used for predicting health risk, as life insurance companies even include it in their predictive models Giorgi, Harding, and Vasconcelos (2021).

Despite the multifaceted use of credit score to both determine and be driven by financial health, there has been little academic work concerning fishing communities and credit scores. While credit scores have been used as a measure of individual and community economic health in response to the implementation of Limited Entry policies in Alaska (Knapp 2011; Cullenberg et al. 2017), this chapter is unique in its scope and scale. Given the high financial risk that harvesters and fishing communities face, this exploratory analysis examining drivers of credit scores provides a groundwork for assessing differential risk in commercial fishing across the West Coast.

In addition to the analysis finding that West Coast harvesters collectively have excellent credit, a key result of this chapter was the lack of significance between income diversification within commercial fishing target species and credit score as a measure of financial health. While income diversification within fishing was not a significant driver of credit score, the more evenly split an individual's income was between fishing and non-fishing sources was marginally significant depending on model controls. The other key result was that community level variables were significant drivers of credit scores, which suggests the importance of community level consideration for managers targeting harvester well-being.

In what follows, I provide a groundwork for evaluating income diversification strategies for commercial harvesters through the credit rating tool of credit scores. I also summarize credit health for respondents to the 2020 West Coast Fisheries Participation survey while assessing limitations to this type of analysis.

4.2 Data and Methods

This chapter relied on purchased SRX plus credit scores from 2020 that were paired with the confidential 2020 West Coast Fisheries Participation Survey respondent data. More information about the survey and pairing it with county BEA data can be found in Chapter 2. While credit scoring algorithms are proprietary and can vary due to differences in their factors such as credit payment history, amount of outstanding debt relative to borrowing limits, depth of credit history, and requests for new credit accounts (Hartley, Mazumder, and Rajan 2019), individual credit scores are generally very similar across the three major credit-reporting agencies (Equifax, Experian and TransUnion). Mean credit scores were calculated for each county that had 3 or more respondents (Figure 4.1).

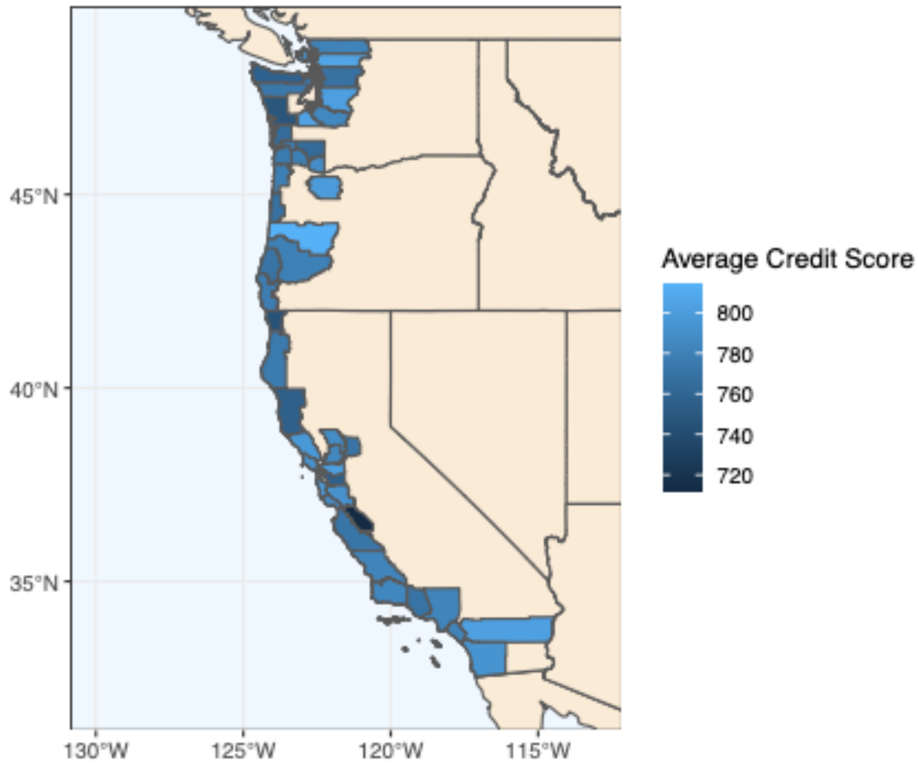

Figure 4.1: West Coast Fisheries Participation Survey respondent's mean credit scores at the county level. Note: only displaying counties with more than 3 respondents.

Credit score models were estimated to examine the success of income diversification strategies along with a series of control variables, described in what follows.

First, I explore whether diversification metrics, which measure potential risk mitigating strategies, affect credit score. Diversification outside of fisheries with non-fishing income, as introduced in Chapter 3, was captured by calculating the absolute distance from 50% for a respondent's personal non-fishing income. Since income diversification in industries outside of commercial fishing is a widely recognized strategy to reduce financial risk (Costanza et al. 2000; Kasperski and Holland 2013), I posit that a the closer an income is to half from non-fishing and the other half from fishing, as measured as the absolute value from 50% non-fishing income, will positively drive credit scores.

A second diversification metric, capturing within-fishery diversification as measured by the mean Effective Shannon Index (ESI) over the years of 2012 to 2016, was calculated using vessel specific fish ticket data (See Chapter 2). I intentionally use the ESI from historical years to avoid the potential endogeneity of 2020 credit scores being utilized to acquire purchasing power for tools and access needed to diversify target species, mean ESI was calculated from 2012 to 2016. I posit that higher ESI, reduces revenue variation and financial risk to closures, therefore increasing credit score.

Demographic variables can be significant determinants of credit score (Henderson et al. 2015), yet many demographic questions were not included in the Fisheries Participation Surveys. Of the questions that captured demographic variables, age, household income, and household size were included in the model iterations. While age does not directly factor into credit agencies' score determining algorithms, it has been found to affect credit score indirectly by capturing an individual's length of credit history (DeNicola 2021). Credit rating agencies also do not use household income as a factor in determining credit score, although it can indirectly affect credit score by influencing determining factors such as credit usage, payment history, and aid in financial recovery from shocks (Cinner et al. 2018). Since the survey collected household income categorically, household income was modeled with the 0-50,000 USD group being the reference level, 50,000 to 100,000 USD as the second group, 100,000 to 150,000 USD as the third group, and greater than 150,000 USD as the fourth group. Household size has been found to be positively correlated with total debt balance (Stobla 2019). Therefore, I theorize that larger households will have lower credit scores.

Community level variables associated with overall economic health were also included in the models, positing that the overall economic health of a community influences an individual harvester's financial health. Therefore, county level unemployment rate and county GDP were again collected from the BEA. State fixed effects were included to account for potential differences at the state level with California set as the reference level. States that were not on the West Coast were filtered from the data as they accounted for no more than 12 respondents.

The full OLS model of credit scores contained both income diversification variables (personal non-fishing income distance from 50% and mean ESI for 2012-2016), the three demographic variables (age, household income category, and household size), the community level economic variables (county level unemployment rate, GDP), and state fixed effects. All of these variables are captured in x_i. Additionally, α captures the constant and ϵ captures the unobserved error. The functional form of this full model is captured in the following equation, where i denotes individuals in the 2020 survey:

$$Credit\ Score_i = \alpha + x_i\beta +$$

To further explore the relationship between the two income diversification strategies and credit score, two nested models were estimated. The first nested model only included both variables capturing income diversification strategies while the second only included personal non-fishing income distance from 50%.

4.3 Results

The majority of 2020 West Coast Fisheries Participation Survey respondents had credit scores well above the 2020 national average of 710 (White 2021b), as shown in Table 4.1. In fact, a majority of respondents were well within the "very good" credit category, which is above 740 (O'Shea 2021). This might reflect the importance of credit for accessing capital in order to invest in commercial fishing equipment and operations. While the grouping of credit scores within the highest ranges is insightful for understanding West Coast harvesters' relationship with credit, it does restrict the predictive ability of the model due to limited variation in the dependent variable which suggests future studies of harvester financial health might face similar limitations.

Table 4.1: Summary statistics for 2020 Fisheries Participation Survey Credit Scores

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Credit Score	914	778.68	40.46	505.00	759.06	805.24	877.00

With the goal of identifying the most parsimonious model without eliminating variables of interest, a step-wise model selection strategy was utilized. The first model included only the two variables of interest, which capture the income diversification strategies. The next specification consisted of the variables of interest along with state fixed effects, which were not found to be significant. For the third specification, the remaining identified controls were also included.

Table 4.2 presents the estimated results of the equations describing credit score for all model iterations. The two nested models are captured in columns 1 and 2 with the full model estimates are captured in column 3.

Table 4.2: Credit Score OLS Model Estimates

	Dependent variable:		
	Credit Score		
	(1)	(2)	(3)
Pers. non-fish income (dist. from 50pct)	-0.31^{***}	-0.30^{***}	-0.19^{*}
	(0.10)	(0.11)	(0.10)
Mean ESI 2012-2016	3.80	3.97	1.51
	(2.65)	(2.66)	(2.60)
Age			0.12
			(0.13)
Household income 50-100K			4.83
			(4.00)
Household income 100-150K			7.26
			(4.68)
Household income over 150K			14.84^{***}
			(4.89)
Household size			-0.81
			(1.56)
County level unemployement			-7.89^{***}
			(1.27)
County level GDP (millions of USD)			0.04^{***}
			(0.01)
Constant	785.04^{***}	785.99^{***}	839.36^{***}
	(5.74)	(5.79)	(15.77)
AIC	6116	6118.3	6077.9
State Fixed Effects	No	Yes	Yes
Observations	601	601	601
R^2	0.02	0.02	0.10
Adjusted R^2	0.01	0.01	0.09
Residual Std. Error	39.06 (df = 598)	39.07 (df = 596)	37.56 (df = 589)

Note: *p<0.1; **p<0.05; ***p<0.01

All of the models found a negative relationship between the distance of personal non-fishing income from 50% and credit score, which suggests individuals who are more evenly diversified with fishing and non-fishing income have higher credit scores. However, the significance found in nested models 1 and 2 ($p < 0.01$) is lost when controlling for demographic and community level variables, which suggests non-fishing income diversification is not a strong predictor. Diversification within fishing is even less strong as a predictor, having no found affect on credit score across the models.

The demographic variables of age and household size were not significant predictors of credit score. These results do not support the hypothesis that age increases an individual's credit history and general financial health for West Coast harvesters. However, household income above 150,000 USD was a significant predictor of credit score ($p < 0.01$). Endogeneity was avoided since salary, debt-to-income ratios, and net worth are not included within credit score algorithms (White 2021a). Since only the highest income category was significant, it suggests significant wealth is required to have an effect on West Coast harvesters' credit scores.

The significance of county level variables suggests that where a harvester lives can affect financial health. A common misconception is that credit reference agencies have "blacklist" addresses, areas that automatically negatively impact credit scores (Salih 2018). While not directly included within the credit report factors, it appears that community level variables do impact harvesters' financial health.

4.3.1 Check Model Assumptions

For the full model, no evidence of multicollinearity between the predictors was found using Variance Inflation Factor (VIF). The VIF for all covariates in the estimation were less than 1.8. The linearity of the model was then confirmed through a residuals vs fitted plot, which displayed no substantial pattern (Figure 4.2: top left). Therefore, a linear relationship between the predictors and the outcome variable can be assumed. Through the scale-location plot (Figure 4.2: bottom left), there is no suggestion of non-constant variances in the residuals errors, therefore, there is no evidence of heteroscedasticity. The normal Q-Q plot (Figure 4.2: top right) approximately follows the reference line, so normality of the residuals can be assumed. From the residuals vs leverage plot (Figure 4.2: bottom right), no outliers that exceed 3 standard deviations were found, therefore, there is no clear outlier influencing the model. Thus, none of the assumptions of OLS regression appear violated.

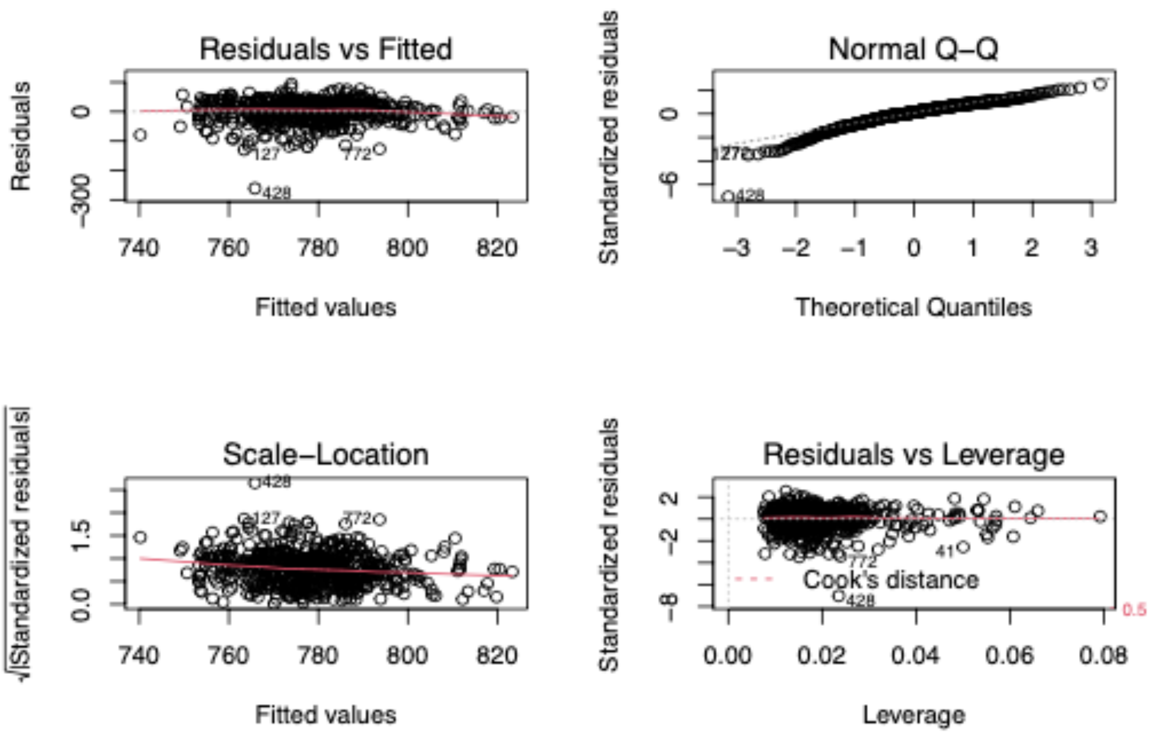

Figure 4.2: Diagnostic plots for the full linear model. Residual vs fitted plot to check model linearity (top left), followed by the normal Q-Q plot to check for normality of residuals (top right), then the scale location plot to check for heteroscedasticity (bottom left), and finally the residuals vs. leverage plot to check for outliers (bottom right).

4.4 Discussion and Conclusion

Despite the evidence presented in this thesis that harvesters face high physical risks and increasing financial risk from fisheries closures (Chapter 2 and Chapter 3), credit scores were high across the 2020 West Coast Fisheries Participation Survey respondents. The vast majority of credit scores were well within the two highest credit score categories. In fact, the significant predictor variables have little determining effect on credit score categorical ranked groups (Figure 4.3). This might suggest that very good credit is a prerequisite to participate in commercial fishing, given that many harvesters must invest heavily in equipment and mortgage vessels. Thus, credit score might be less useful as an indicator of financial health for commercial harvesters than for the general population. Additionally, this result could raise concerns of equity and who can enter commercial fishing given credit scores have been found to be biased against demographic variables such as race and gender (Henderson et al. 2015). Future work should consider including more demographic variables when modeling credit scores given the significance of the constants across the model iterations.

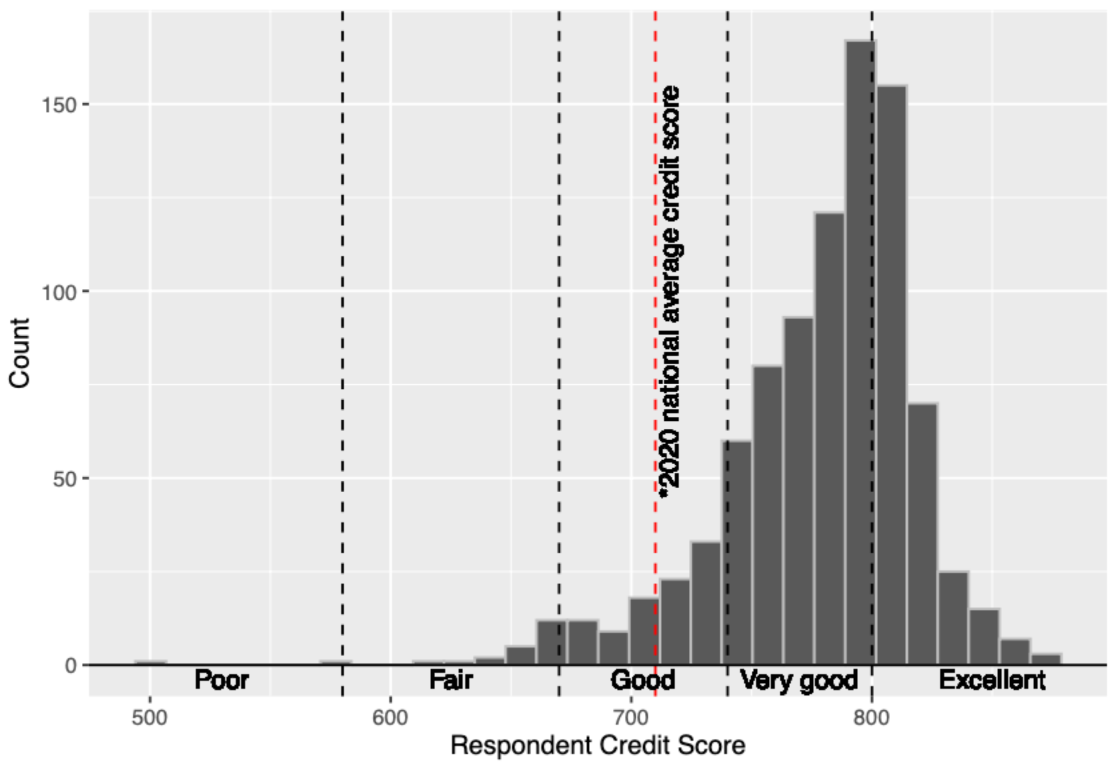

Figure 4.3: West Coast Fishery Participation 2020 Survey respondents credit scores in comparison with the 2020 national average score of 710 and credit score range classifications overlayed.

My model supports the findings that community level variables can be significant drivers of individual financial health (Nichols, Mitchell, and Linder 2013). Despite the common misconception, credit reference agencies do not consider addresses when calculating credit scores (Salih 2018), thus the results that both community economic well-being variables, unemployment rate and GDP, were found to be drivers of credit score should not be an artifact of reverse causality. Also, since there is no evidence of multicollinearity in my model, unemployment rate and GDP are not reducing credit score by directly limiting diversification and/or household income.

Instead, these macroeconomic factors are likely reflecting the strength of an individual's social safety net. The reliance on one's community during fisheries shocks has been documented along the West Coast, with over 15% of harvesters in Oregon and California and over 30% of harvesters in Washington borrowing money from friends or family to cope with the 2015 harmful algal bloom (HAB) fisheries closures (Moore et al. 2020). My results also support the findings that macroeconomic effects of unemployment rate can exceed the mere sum of individual unemployment effects (Rendon and Bazer 2021).

This study also offers a new approach for empirically comparing income diversification strategies. As introduced in Chapter 3, diversification within commercial fishing and other industries has been promoted as a way to reduce harvester financial risk as measured through reduced fishing income variability (Kasperski and Holland 2013; Anderson et al. 2017). In contrast, I examine the effectiveness of these strategies in improving financial health as measured with credit scores. The model's results support the benefits of non-fishing diversification, by finding that how evenly an individual earned income from both fishing and non-fishing work marginally improved credit score. While not statistically significant, the model suggests income diversification outside of fishing might be a useful strategy for increasing financial health and should be further examined in future work.

Finally, my model found that diversifying within fishing did not affect credit score. While there is evidence from Alaska and the West Coast that higher levels of fishing diversification can substantially reduce income variability, income diversification within fishing can come with increased costs, such as purchasing different gear or licenses, that might offset the benefits (Kasperski and Holland 2013). There are also risks associated with fishing in unfamiliar areas and potential difficulties for achieving profitability (Anderson et al. 2017). When considering the results of my model, it appears that diversifying target species does not drive credit score. If future studies find similar results, then the increasing restrictions and decreasing diversification of West Coast fishing vessels as found by Holland and Kasperski (2016) might have a more limited impact on financial health as individuals with income variation are able to maintain credit scores. This raises many questions concerning how income diversity can be most effectively implemented to mitigate risk. Regardless, the high non-monetary value that harvesters place on being able to fish as found in Holland, Abbott, and Norman (2019) suggests that financial health alone is far from the full story for individual and community well-being. In conclusion, risk science is, and will continue to be, a key aspect of the paradigm shift to ecosystem-based fisheries management (EBFM) that is pioneering how we consider natural resources in the face of so many uncertainties.

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