# Not by Fishing Alone:
# Non-Fishing Employment and Income for US West Coast Fishers

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**Abstract**

Income diversification is an important aspect of financial security among individual fishers, who generally face high annual fluctuations in their income levels. While prior studies have analyzed the importance of diversifying *within*-fisheries income streams (e.g., across species groups, or region), the role of income from non-fishing occupations as an additional source of diversification has received little empirical attention. We link fisheries landing data to survey responses among 1,230 individual fishers living in the Continental US West Coast to analyze trends and correlates of individual fishers choosing to earn non-fishing income. We find that predictors capturing the opportunity cost of not fishing, pecuniary factors, and within-fishery diversity metrics significantly influence the probability that fishers earn non-fishing income. Our results indicate an overall tradeoff between within-fishery with non-fishery income diversification choices; but that this tradeoff may be weaker for particular non-fishing occupation types and at particular times of the year.

*Keywords:* fishing livelihood, non-fishing income, diversification, vulnerability

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# 1. Introduction

Fishing is a financially risky way to earn a living. Compared to many other professions, fishers face unusually high variability in their income levels (Kasperski and Holland, 2013). This variability is influenced by a range of interconnected economic (e.g., fuel and harvest prices), environmental (e.g., variations in targeted stock's status and accessibility), and policy (e.g., spatial and seasonal closures, restrictions on access) factors which have, in some cases, become increasingly unpredictable due to climate change and it's oceanographic feedbacks. Examples of these shifts include, but are not limited to: spatial and temporal shifts in species distributions, altered growth and recruitment patterns, algal blooms, ocean acidification, and extreme weather events (Schwing et al., 2010; Sumaila et al., 2011; Pinsky et al., 2013; Black et al., 2014; Moore et al., 2020; van der Sleen et al., 2022). These biophysical shifts, their associated regulatory responses, and market-side fluctuations in prices can significantly exacerbate the volatility and timing of individual fishers' income streams (Sethi, 2010). Understanding how individual fishers and fishing communities can be resilient to these changes in financial risk is thus of growing management interest.

One area of recent research focuses on how individual fishers can reduce their financial risk by diversifying their fishing activities across multiple species (Kasperski and Holland, 2013; Sethi et al., 2014; Finkbeiner, 2015; Cline et al., 2017; Fuller et al., 2017). This 'portfolio' approach has been extended to think about other margins of income diversification, including space (Gonzalez-Mon et al., 2021) and time (Abbott et al., 2022). While these margins do frequently help to reduce fishers' financial risk, focusing solely on diversification opportunities within the fishery misses a potentially critical form of financial risk reduction: income diversification from *non-fishing* occupations (i.e., livelihood diversification), both for individual fishers and members of their household (Szymkowiak, 2020). In fact, livelihood diversification may be a more effective form of financial risk reduction among individual fishers if their non-fishing income streams are decoupled from fishery-specific income shocks. Further, depending on the flexibility and timing of non-fishing employment opportunities relative to fishing opportunities, within-fishery diversification may come at the cost of diversification outside of the fishery. Thus, within-fishery diversification metrics may provide a partial, or even misleading, picture of vulnerability to fishery-specific financial shocks.

Livelihood diversification is not a new concept. Many studies have called for increased livelihood diversification in developing frameworks for coastal community resilience (Allison and Ellis, 2001; Badjeck et al., 2010; Pinsky and Mantua, 2014; Ojea et al., 2017). However, much of this work has focused on small-scale, artisanal fisheries (e.g., Cinner and Bodin, 2010; Martin et al., 2013; Deb and Haque, 2016; Shaffril et al., 2017; Abu Samah et al., 2019), often in a Global South context where the importance of flexible access to fisheries as a 'pro-poor' form of insurance is often emphasized (Béné, et al., 2010; Wilen, 2013). Despite the growing literature on within-fishery diversification in the non-artisanal context, there has been very little examination, and even less quantitative analysis, of the role and magnitude of non-fishery income (NFI) streams in fishers' livelihood portfolios and how NFI interacts with fishers' within-fishery choices.

In this study, we conduct the first empirical analysis of the patterns and predictors associated with livelihood income diversification among fishers in a large marine region with a number of large-scale commercial fisheries: the California Current Large Marine Ecosystem (CCLME). In particular, we distinguish between fishers who earn all of their income from fishing activity from those who earn some NFI, and further distinguish between the types of non-fishing occupations contributing to livelihood income diversification. We summarize patterns in this livelihood diversification behavior across geographic gradients, species targeted, and seasonality. We then test the influence of a range of predictors, including within-fishery diversification and effort variables, social-psychological indices, and demographic characteristics on the incidence and intensity of earning NFI.

The paper is organized as follows. In the following section, we present a brief background outlining the types of factors that may be relevant to fisher's livelihood diversification choices that have been tested in related lines of literature. Section three outlines our data sources and methodological approach. We present our results and key findings in section four and provide a discussion of the implications of our results in the final section.

## 2. Background Literature and Hypotheses

In order to understand the prominence and role of livelihood income diversification for fishers, we first consider the factors which may be associated with an individual fisher's interest and ability to diversify across non-fishery occupation types. Although our focus is not on fishery exit, it is reasonable to assume that many of the factors associated with exit may also influence an individual's decision to earn some income from non-fishing occupations. Exit decisions have been explored in both developed (Stewart et al., 2006; Pita et al., 2010; Tidd et al., 2011; Crosson, 2015) and developing nation contexts (Cinner et al., 2009; Daw et al., 2012; Slater et al., 2013; Abu Samah et al., 2019; Chen et al., 2020).

One set of factors that has been robustly connected to exit behavior is the opportunity cost of exit relative to potential non-fishery returns. These factors have been measured by within-fishery revenue levels, expected revenue levels in coming years, amount of fishery capital owned, and the potential income from non-fishing occupations in both developed (Pradhan and Leung, 2004; Crosson, 2015) and developing country contexts (Cinner et al., 2009). There may also be direct costs and constraints to earning employment from non-fishing occupations. For example, geographic location and migration ability are important to consider, as more isolated coastal communities may have a lower number and smaller variety of available non-fishing jobs than in larger metropolitan areas (Panayotou and Panayotou, 1986; Daw et al., 2012). We hypothesize that fishers with higher opportunity costs of not fishing would be associated with a lower incidence and intensity of earning income from non-fishery occupations.

Demographic correlates of exit, such as age, education, and number of household members have also been examined in many contexts (Terkla et al., 1988; Pollnac and Poggie Jr, 1988; Stewart et al., 2006; Pita et al., 2010; Muallil et al., 2011; Crosson, 2015). Individuals with higher education levels are more likely to be qualified for a wider range of highly paying non-fishing occupations. Similarly, younger individuals may have a greater propensity to pursue a wider range of non-fishing occupations (e.g., physically intense positions). A larger household size may have an indeterminate effect; having income from other household members may lessen pressure on a fisher to exit in bad times, but a larger household may also place greater pressure on fishers to maintain their fishery income. We hypothesize that younger, more educated fishers would have a stronger association with the incidence and intensity of earning income from non-fishery occupations.

Beyond economic considerations, the role of cognitive, cultural, and social considerations has been shown to directly influence fisher's reluctance to pursue non-fishing work (Pollnac and Poggie, 2006; Pita et al., 2010; Holland et al., 2020; Arias Schreiber and Gillette, 2021; Roscher et al., 2022). Holland et al. (2020) show that individual West-Coast fishers were less likely to work other professions in response to a closure if they had higher levels of identity as a fisher, social capital in fishing, and job livelihood satisfaction. For many individual fishers, professing personal attachment to fishing and fishery-specific social capital can raise the felt costs of changing occupations. We hypothesize that fishers with higher stated levels of social capital, identity, job quality satisfaction, and job livelihood satisfaction as a fisher would be associated with a lower incidence and intensity of earning income from non-fishery occupations.

While fishery exit has been extensively studied, relatively little attention has been paid to the non-fishing occupations pursued by exiting fishers. Stewart et al. (2006) outline the profile of job types that those exiting the Australian fishery worked in response to a regulatory change as primarily (46%) off-water fishing occupations (e.g., processing, aquaculture, boating related), with an additional 12.5% moving into farming. Zheng et al. (2021) develop a theoretical framework distinguishing between three types of job-transfer pathways among Chinese fishermen: intra-industry transfers (e.g., moving to mariculture), inter-industry transfers (e.g., part-time fishing), and out-of-industry transfers. Roscher et al. (2022) reviews livelihood diversification in artisanal fisheries contexts and distinguishes between broad categories of non-fishing activities, including agriculture, aquaculture, and non-natural resource type occupations. We note that the types of occupations available to and demanded by fishers are likely to vary significantly between developing and developed country contexts.

Another factor that has escaped empirical treatment is the role of seasonality in both fishery and non-fishery employment for fishery exit and livelihood diversification. Seasonal availability and quality of target species, market conditions, and regulations can all produce significant intra-annual variation among fishing communities in multi-species settings (Clark, 1980; Homans and Wilen, 2005; Bjørndal and Munro, 2012; Birkenbach et al., 2020), while the seasonality of NFI opportunities and wages may play an important role in fisher decision making (Ben-Hasan et al., 2019), creating the potential for greater or lesser complementarity between fishing and non-fishing employment.

# 3. Data & Methods

## 3.1. Data

The primary data for this analysis come primarily from two sources: 1) a survey of active US West Coast fishers and 2) their detailed fishery landings data.

### 3.1.1. Fisher survey data

The first data source is a fisheries participation survey administered in 2017 (Holland et al., 2020) based on a sampling frame of 2842 vessel-owners with commercial landings in Washington, Oregon, or California during the 2015 or 2016 season. The survey data contain 1,437 responses (51% response rate), and Holland et al. (2020) found no statistical evidence of non-response bias based on observable demographic traits or geography. From these responses, we extract data about NFI earning levels, non-fishing employment decisions, and demographic information for each unique vessel-owner (the unit of analysis).[1]

[1] We provide the key NFI related survey questions in Appendix S.1.

The first variable of interest is the *NFI share* for each vessel-owner, defined as the proportion of a respondent's personally contributed income to the household (not household income overall) earned from non-fishing occupations, as indicated by their direct survey response. Respondents were asked to estimate this share based upon the "last 3-4 years" so that this metric reflects an average NFI share over recent years.

Respondents that reported a positive NFI share were asked an open-ended question about the type of work they did over this 3-4 year period in addition to their commercial fishing occupation. We manually coded these responses into occupational categories using the 2010 Standard Occupation Classification (SOC) of the US Bureau of Labor Statistics.[2] We coded responses at the minor group level (96 levels); however, given the sparsity and potential for miscoding of responses at this level, we only analyze results at the level of major SOC groupings (23 levels). We further limit our analysis to the top four demanded professions by SOC's major groupings: construction work (n = 127), transportation work (n = 66), management work (n = 63), and fishing/farming/forestry work (n = 61), with the remaining occupations grouped into an "other" group (n = 259).

For each of these major occupational groups, we provide a few examples of the most common open-ended responses.[3] "Construction" itself was the dominant response within the construction category. "Trucking" and "boat captains" were common transportation responses. "Rental income" and "owners" of restaurants/businesses were common responses in management. Fishing/farming/forestry responses were fairly evenly split among "farming", "logging", as well as some fishing related occupations such as "fish processing" or "sport fishing." We note that the "fishing" aspect of this category is not representative of earning income from commercial fishing itself, but from other related peripheral activities that we qualify as non-fishing occupations. There were a wide range of responses in our "other" category, with a few responses such as "real estate" and "teaching" being common.

[2] https://www.bls.gov/soc/2010/2010_major_groups.htm

[3] We include a sample crosswalk of our manual coding methods in supplementary material Table S.1 with more examples of types of open-ended responses coded to each of the SOC major groupings.

We also collected data on the seasonal frequency of earning NFI. Conditional on earning any NFI, the survey asked how frequently individuals earned NFI in each distinct season (quarter) of the year: January - March, April - June, July - September, and October - December. Responses were given as a choice between "Always", "Mostly", "Sometimes", and "Never". We recode each non-empty response as either a high ("Always" or "Mostly") or low value ("Sometimes" or "Never") *NFI frequency* for each season.

Moving beyond NFI-specific questions, we also utilize four composite indices constructed from the survey that capture several distinct social-psychological factors related to fisheries specific social capital, strength of identity as a fisher, satisfaction with non-pecuniary aspects of fishery job quality, and fishery livelihood satisfaction. These metrics are incorporated directly from Holland et al. (2020), who utilize confirmatory factor analyses from a large number of survey questions to create these indices for each vessel-owner. Each of the indices is normalized to have a mean of zero and standard deviation of one in the overall sample.

Finally, we collect several other demographic variables from the survey, including age, number of household members, number of crew members, household income level, and the zip-code in which the vessel owner resides for more than half of the year.

#### 3.1.2. Fishery landings and geographic data

We use confidential trip-level fish ticket data with detailed landings information for all commercially registered vessels operating on the U.S. West Coast between 1981-2016. We are able to match unique survey responses to vessel registration numbers in order to create a cross-section of stated non-fishing behaviors from the survey responses along with the observed within-fisheries revenue earned from the fish ticket data.

From these data, we calculate for each vessel owner the total, and species group specific, ex-vessel revenue earned and total effort days between 2012-2015.[4] To reduce the many dozen distinct species pursued by fishers into a tractable list, we use a 26

[4] This four year time frame matches the span of the NFI-related survey questions, but omits the year 2016 in which we only have partial fish-ticket data.

species classification system employed in Abbott et al. (2022) for the CCLME.[5] We also calculate the total, and species group specific *seasonal* ex-vessel revenue earned by each vessel-owner, where seasons match the quarterly definitions employed in the survey. In many of our visualizations, we present results for the top seven species groups in terms of total ex-vessel revenue earned as: Dungeness crab, lobster, salmon, pink shrimp, sablefish, market squid, and albacore. These species account for 84% of the total revenue in our sample, and we group all other species into an aggregate "other" category.

We utilize these data to calculate annual species, space (county), and time (week of year) revenue diversification metrics for each vessel-owner in the landing year 2015. Following the methods in Abbott et al. (2022), we use the Shannon diversity index (Jost, 2006):

$$exp[-\sum_{j=1}^{J} s_j * \ln(s_j)]$$

where $s_j$ is the share of revenue in any given species, spatial, or temporal bin. Species bins are given by the 26 previously defined categories. Spatial bins are defined by county of landing among the 53 coastal counties in our sample. Temporal bins are determined by week of the year.

To provide a metric of the level of relative financial risk experienced by fishers, we use the coefficient of variation (CV) for ex-vessel revenue earned fishing across the 2012-2015 time period for each vessel-owner. Defined as the ratio of the inter-annual standard deviation to the mean, CV provides a normalized measure of financial risk that has been widely adopted in prior studies (e.g., Kasperski and Holland, 2013; Sethi et al., 2014; Holland et al., 2017).

Using the zip-code provided by each vessel owner, we link each respondent to the county and state in which they reside. We then use the US Center for Disease Control's

[5] These species groups are: California halibut, bay clam, Dungeness crab, herring, lobster, market squid, nearshore species, other coastal pelagic, other crab, other groundfish, other shellfish, other shrimp, other species, Pacific halibut, Pacific sardine, pink shrimp, rock crab, sablefish, salmon, scallop, sea cucumber, sea urchin, spot prawn, swordfish and shark, tuna (listed, more precisely in our case as albacore), and whiting.

Urban Rural Classification Scheme[6] to determine each county's location along the urban-rural gradient based on a 1-6 ranking, where lower numbers are larger metropolitan counties and higher numbers are micropolitan and non-core counties.

Our final dataset utilizes 1,230 of the 1,437 vessel owners. We drop 82 responses with missing information for personal income, 57 that attributed all of their non-fish income to Social Security, 27 which gave inconsistent information across their personal and household incomes, 36 with mismatches on the vessel-owner coding between the survey and fish ticket data, and 5 outside of the contiguous US.

## 3.2. Methods

Our analysis is designed to address two, primarily descriptive, research questions:

1. What are the patterns of NFI earning across geography, species, and season?
2. What are the significant correlates of variability in NFI incidence and intensity across fishers?

### 3.2.1. Question 1

*What are the patterns of NFI earning across geography, species, and season?* To address the first question, we present a series of visual summaries illustrating the breakdown of vessel owners who do and do not earn NFI across different geographic gradients, species types targeted, and seasonality in their revenue streams. We first group vessel-owners into four distinct regions: Washington, Oregon, Northern California, and Southern California. We define Southern California as the southern-most ten counties in the state.[7] We also define three distinct groupings for the Urban-Rural gradient as "Rural" (those

[6] https://www.cdc.gov/nchs/data access/urban rural.htm

[7] Imperial, Kern, Los Angeles, Orange, Riverside, San Bernardino, San Diego, Santa Barbara, San Luis Obispo and Ventura counties.

counties which are micropolitan or noncore), "Suburban" (medium and small metropolitan counties), and "Urban" (large and fringe large metropolitan counties).[8]

In totality, these figures allow us to examine whether there are notable differences in fishery-specific dependence across fishing specialists vs. NFI earners and across NFI occupational categories. We also examine whether these differences vary in important ways across regions and across the four seasons (quarters) of the year.

### 3.2.2. Question 2

*What are the significant correlates of variability in NFI incidence and intensity across fishers?* To address this question, we first define three distinct NFI groupings: the **zero NFI share** group, the **low NFI share** group (i.e., those with an NFI share > 0 and < 0.5), and the **high NFI share** group (i.e., those with an NFI share ≥0.5). In Table 1 we present the mean ($\mu$) and standard deviation ($\sigma$) for our key variables within each NFI group. We also conduct t-tests for differences in means between the zero and low and zero and high NFI groups respectively in columns 5 and 6, where the variables included in this comparison are based upon the demographic, social-psychological, and operational characteristics we justify in greater detail in the models below.

We then estimate two distinct regression models to jointly examine the correlates of vessel-owners choosing to earn NFI, and the degree to which they do so. The first model addresses the correlates of the probability that an individual vessel-owner earns *any* NFI, so that the binary dependent variable = 1 for a positive level of personally-contributed NFI but = 0 otherwise. Rather than estimate a logit or probit model, we instead estimate a linear regression model (known as a linear probability model or LPM). While not the best choice for observation-specific predictions of probabilities, the LPM has the advantage over other binary-choice models that it's coefficients are directly interpretable as the average marginal effect on the probability of a one unit change in the independent variables (Angrist and Pischke, 2008) and is therefore ideally suited to our purposes. We

[8] We note that for any figures with our regional gradient, we omit 8 vessel-owners who resided outside of the West Coast states.

utilize heteroskedasticity robust standard errors to account for the inherent heteroskedasticity of the LPM (Angrist and Pischke, 2008).

We estimate four increasingly comprehensive, nested model specifications to test the hypotheses discussed in section 2 as well as the associations between within-fishery financial risk, and diversification, with the incidence and intensity of earning NFI. All models include the four social-psychological measures of fishery job satisfaction (identity, social capital, job quality satisfaction, and job livelihood satisfaction). We also include two demographic characteristics, age and number of household members.[9] In our second specification, we add the number of crew members employed and the total number of days fished by individual vessel-owners. These variables capture proxies for the overall opportunity costs of non-fishing income and the degree of commitment (both in terms of effort and as an employer) to the fishery. We also include the CV measure of within-fisheries financial risk, since within-fishery risk exposure may affect the tendency to pursue livelihood diversification. In the third specification, we add the within-fisheries species, space, and time diversity measures as additional predictor variables in order to distinguish the role of within-fishery risk on NFI as distinct from diversification decisions that may affect this risk.

The analysis for the first research question establishes that there are notable differences in NFI across space. These distinctions may arise from measurable factors (e.g., unemployment rate, rural vs. urban, or the presence of employers across different sectors) or from unobservable dimensions of the local labor market or fisher characteristics. To make our estimates robust to this potentially long list of factors, we include spatial dummy variables (i.e., spatial fixed effects) to absorb both channels of impact. In Models 1-3 we include state fixed effects, while in Model 4 we instead utilize county fixed effects to provide a finer degree of control for underlying patterns in NFI determinants.

To estimate the model of NFI intensity, conditional on positive NFI, we regress the share of personally-contributed household income obtained from NFI on the same

[9] We note that we do not observe individual fisher's education levels.

correlates as in the NFI presence model (NFI share), including the same state and county fixed effects. This 'second-stage' model is estimated for only those respondents with a positive NFI level. We utilize heteroskedasticity-robust standard errors for all specifications.

All variables in the regression models are normalized to a mean equal to zero and a standard deviation equal to one. This eases the comparison across regressors defined on inherently different scales. For Model 4 in both our first and second stage regressions, we re-run the model with no intercept and extract the coefficients for the county level fixed effects. We map their de-meaned values for all counties to see whether there are any geographic patterns in NFI extent or intensity that are unexplained by the model regressors.

We note that we are attempting to examine associative, rather than causal, relationships with our modeling approach, which is appropriate given that we only have a single cross section of NFI data from the survey. All of the tables, figures, and regression models used for these analyses were created using *R* statistical software, with the *tidyverse*, *ggplot2*, *broom*, and *estimatr* packages.

# 4. Results

## 4.1. Question 1: NFI patterns by geography, species, and season

### 4.1.1. Geography and NFI

The breakdown of 2012-2015 fisheries revenue across region of residence is: 18% in Southern California, 31% in Northern California, 20% in Oregon, and 31% in Washington. Over half of fishing revenue (52%) is earned by fishers residing in rural areas, with 22% and 26% coming from urban and suburban areas, respectively.

Figure 1 presents the share of surveyed vessel-owners earning their personal income solely from fishing (black horizontal lines) and the shares by occupational category for those with NFI across regional and urban-rural strata. We find a much greater share of fishers with no NFI in Washington State – 64%, compared to 50% or less elsewhere. Such specialized fishers are also much more common in rural areas, comprising 62% of surveyed individuals there relative to 44% in more urbanized areas.

Fishing revenues are far more concentrated among respondents without outside employment than their share of the sample might suggest; more than 75% of revenues accrue to "full-time" fishers when they are only 51% of this sample (Figure 1). The distribution of revenue share mirrors that of total fishers, with more northerly regions having a greater concentration of fisheries revenues among full time fishers than in California. Revenues to suburban and rural respondents are more highly concentrated among fishing specialists than for urban fishers. This trend is particularly strong in suburban areas, where the share of revenues to fishing-only respondents (77%) is much larger than their population share (44%).

Turning now to the patterns of non-fishing occupations across geographic gradients, we find that over half of respondents in all regions and degrees of urbanization work in either the construction, fishing/farming/forestry, management, or transportation fields (Figure 1). Construction is uniformly the largest occupation share, and is more common as a source of employment in California, particularly Northern California, than in the Pacific Northwest states, where relatively more respondents with NFI employment work in the fishing/farming/forestry or transportation industries. Construction work is also more common for respondents residing in suburban areas than those in either rural areas (where fishing/farming/forestry and transportation jobs are more common) or urban areas.

Figure 1 also shows that the contribution of fishers with different NF occupational categories to fishing revenues differs a great deal across occupation type. Most notably, there is a very high relative contribution to fishing revenue from those working management jobs, compared to the share of positive-NFI respondents in management occupations. Vessel-owners employed in management professions contribute 47% of fishing revenues to positive-NFI fishers in Oregon and 39% in rural areas, whereas no more than 12% of fishers with NF employment work in management in either case. This lopsided relationship may be explained by the fact that many management occupations generate income that is heavily dependent on ownership interest rather than labor commitment (e.g., rental income) or that entails fairly flexible time commitments – allowing substantial time toward pursuing fishery income.

A similar asymmetry exists for fishers who work transportation jobs in Southern California. This group earns 25% of fishing revenue among positive NFI earners in the region compared to their regional share of positive-NFI fishers of only 11%. Another interesting trend is the relatively modest overall contribution to fishing revenues from vessel-owners working construction jobs, relative to their share of the total number of fishers with NF employment. With the exception of urban areas, the contribution to fishery revenues for NFI earners from those working construction occupations is lower than their share of NFI earners across all geographic gradients.

Lastly, figure 1 shows that the contributions of individuals in occupational categories to fisheries income differs considerably from the breakdown of workers across these categories. Whereas construction is the most common NF occupational category, fishers with construction employment account for a comparatively small share of fishery income in all regions. Conversely, fishers with management jobs comprise a much larger share of fisheries revenues in California and Oregon than their small share of positive-NFI fishers would suggest. Again, an explanation for this phenomenon is that the non-wage nature of income for many management income sources may provide fishers with greater flexibility to fish more intensively.

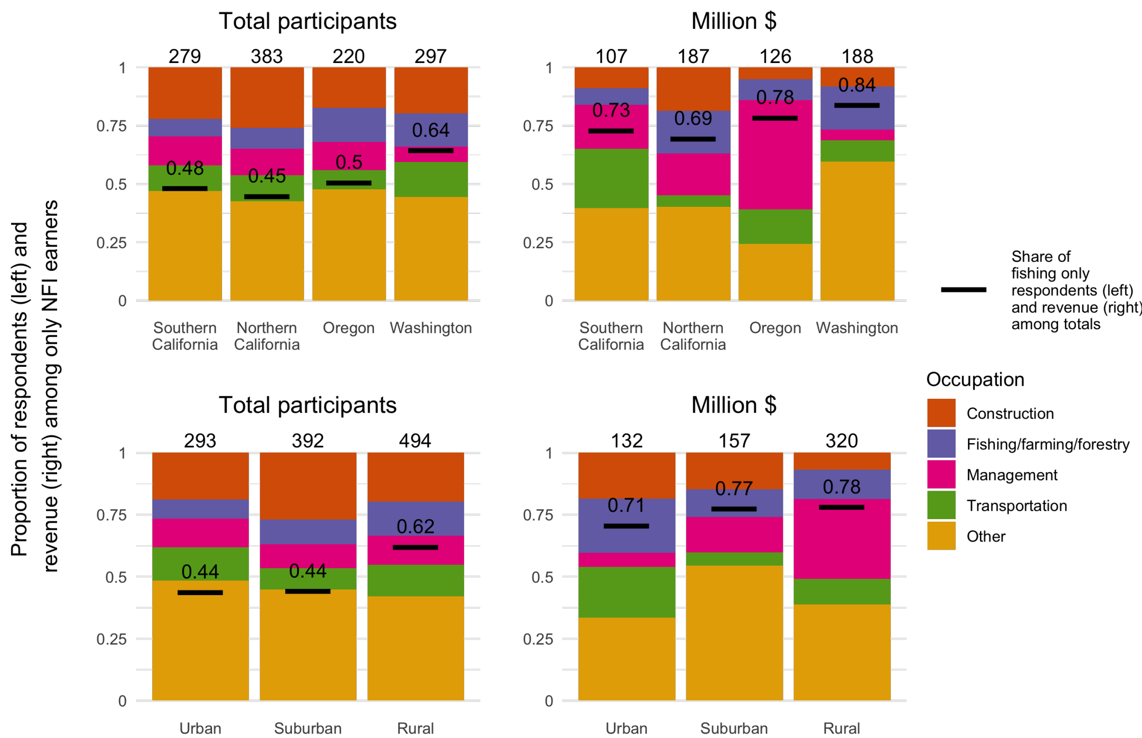


Figure 1: Left: Proportion of number of vessel-owners in each occupational group among all non-zero NFI earners (left axis) in each region (top) and rural-urban gradient (bottom). Black bars indicate % of vessel owners with fish only income in each region and rural-urban gradient, among all respondents. Total number of vessel-owners across our regional and rural-urban gradients are printed above each bar. Right: proportions and totals listed in terms of total fishing revenue, rather than vessel-owners, for each region and rural-urban gradient.

### 4.1.2. Species and NFI

Figure 2 considers the distribution of fisheries revenue by species for specialized and NFI earning fishers across regions. Among fishers in Southern California, we find that NFI earners rely upon lobster for a much higher share of their fisheries income (41%) compared to those only earning fishing income in the region (18%). Interestingly, in Northern California, there does not appear to be large disparities in species dependence across those earning NFI vs. specialized fishers. In Oregon, those earning NFI depend upon salmon (16%), pink shrimp (17%), and albacore (18%) revenues at moderately higher rates than those earning only fishing income (8%, 13%, 12% respectively), whereas fishing specialists earn much more of their revenue from Dungeness crab (38% vs. 27%). Of fishers in Washington, those earning

NFI obtain more of their fishery income from salmon (17%) than those earning fishing income only (8%), and notably, harvest zero market squid relative to full-time fishers (20%).

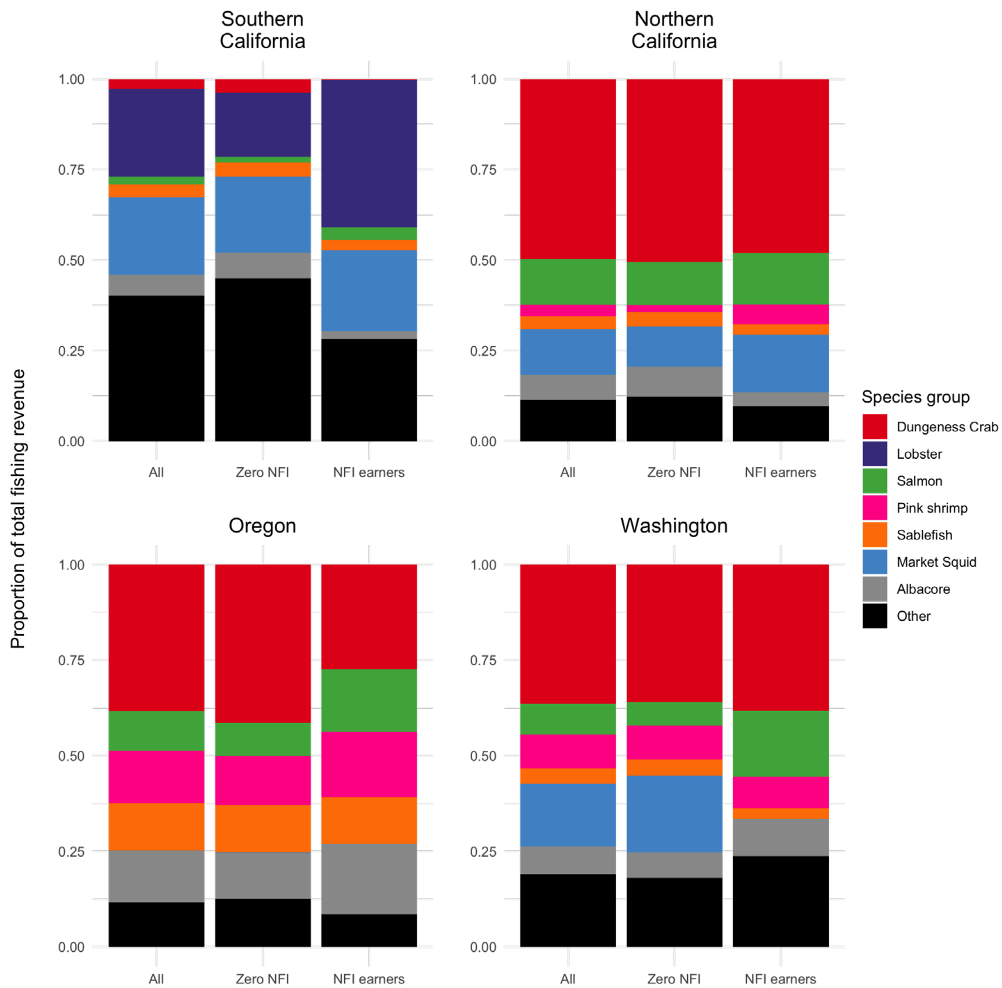


Figure 2: Breakdown of species targeted by region across our full sample, those only earning fishing income, and those additionally earning NFI.

Figure 3 assess the share of total species-specific revenues earned by each NFI occupation group – a rough measure of their "footprint" in the fishery. Part-time fishers have the largest presence within the lobster, salmon, and pink shrimp fisheries, earning 47%, 35%, and 27% of revenues, respectively. Beyond these species, the distribution of revenues between NFI earners vs. specialist fishers is consistent, with NFI earners comprising roughly 20% or less of revenues. Importantly, while Dungeness crab is a high proportion of part-time fishers' revenues across occupational categories in all regions except Southern California (Fig. 2), fishers with NF income comprise a small proportion of Dungeness crab harvest.

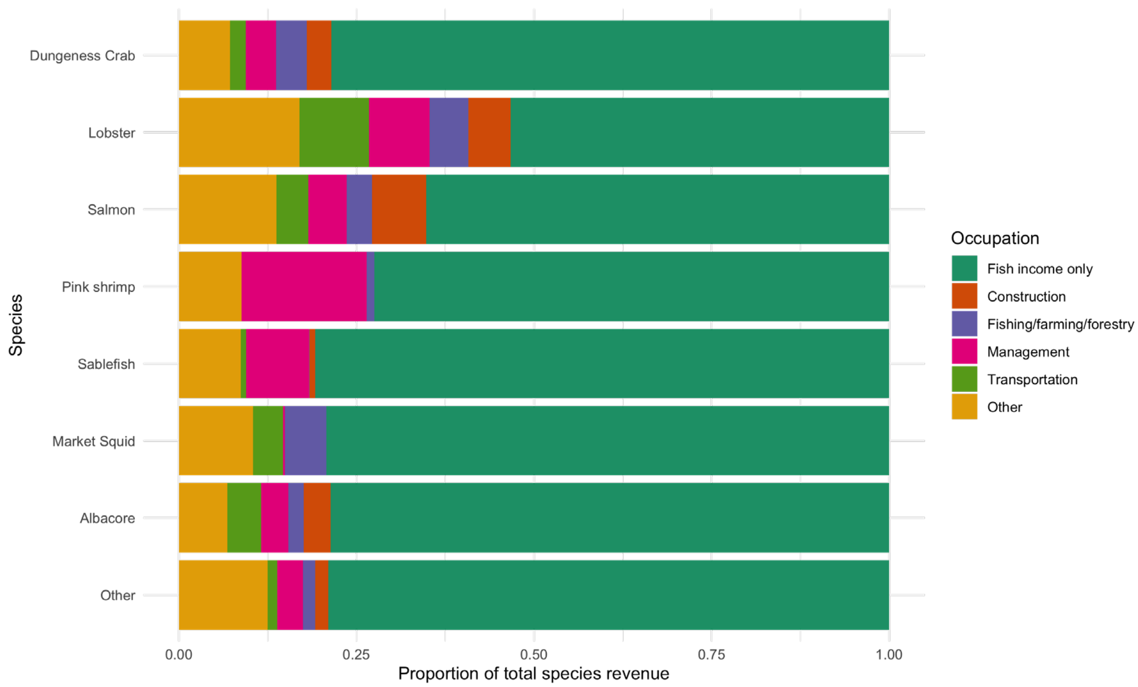


Figure 3: Proportion of total revenue earned within each species group by different occupations.

#### 4.1.3. Seasonality and NFI

In Figure 4, we present the seasonal trends in total revenue, and species-specific revenue for each occupation type, including fishing exclusively. For each NFI occupation, we add trend lines representing the proportion of high NFI frequency earners within each season for that occupation (i.e., whether each individual indicated earning NFI "always" or "mostly" in that season). Generally, the highest revenue fishing seasons are in the late summer and fall for most occupation groups, with the spring months being the lowest. Those working management occupations have the most evenly distributed revenue stream from fishing through the year, perhaps reflecting the aforementioned flexibility of time commitment associated with many sources of management NFI. The seasonal pattern of fishing revenues for those working fishing/farming/forestry and construction jobs most clearly matches that of full-time fishers, with a significant share of income coming in the first quarter, primarily from Dungeness crab. However, aside from the strong role of crab, the drivers of the seasonal rhythms of fishing/farming/forestry and construction are distinct. Spring and summer revenues for fishers engaging in construction are heavily dependent on salmon and albacore, whereas fishers pursuing outside work in the resource sector are less dominated by salmon in these months, with market squid playing an outsized role from July-September.

Comparing seasonality of fishery revenues with the seasonality of respondents' high NFI frequency, we find divergent results across occupational categories. First, both management and other occupations exhibit a higher mean share of NFI frequency, with 60% or more consistently reporting "always" or "mostly" earning NFI across all periods, compared to levels around or below 50% for other NFI sources. Secondly, fishers with construction as their source of NFI exhibit a generally declining trend in NFI frequency over the year – a pattern that roughly inversely coincides with trends in fisheries revenue for this group. This pattern is consistent with fishers substituting between their NFI opportunities and time spent fishing. Finally, fishers working in the fishing/farming/forestry sector see their peak NFI frequency in the summer months when their fishery revenues also peak. This may be indicative of a more complementary relationship between fishing and employment in fishery related sectors (e.g., fish processing). Overall, the descriptive evidence for a substitution effect between fishing and non-fishing income is weak in our data, although it may exist for those in construction.[10]

[10] Beyond this graphical analysis, in unreported regression results we attempted to model seasonality of NFI and found a statistically significant, but practically tiny, negative relationship between seasonal NFI presence or intensity and activity/revenue in fisheries in the same quarter.

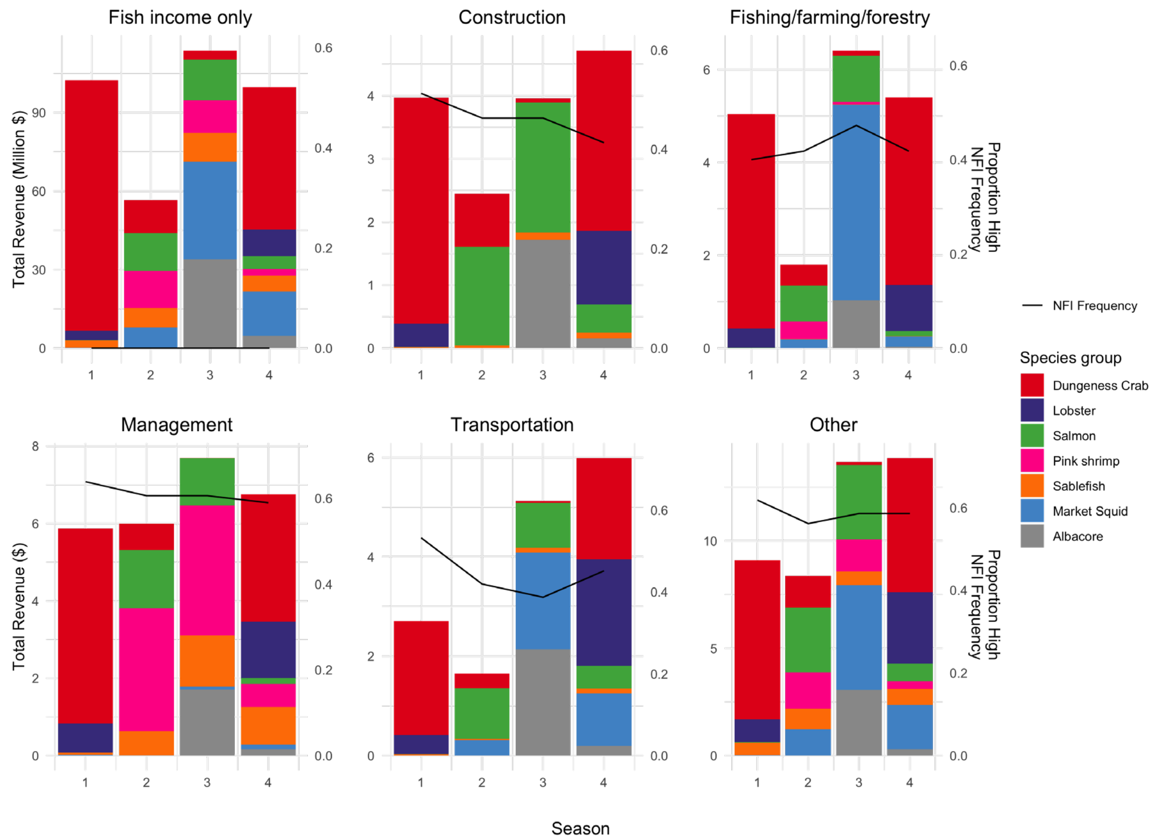


Figure 4: Total revenue earned by each occupation group in each season (left axis) and proportion of high frequency NFI work (i.e., working "always" or "mostly") in each season by each occupation group (right axis). Omitting "other" species groups.

## 4.2. Question 2: Correlates of NFI incidence and intensity

### 4.2.1. Summary statistics: differences across NFI shares

Table 1 illustrates a number of important similarities and differences across individuals with varying tendencies toward non-fishing income. We find little evidence of statistically significant differences in demographic variables (age and size of household) across NFI share levels. Individuals with a non-zero but low NFI share are more likely to have a low (<50K) household income relative to individuals with either a zero or high NFI share, while individuals with a high NFI share are weakly more likely to be part of households with moderate incomes (between 50K and 125K). Interestingly, the fraction of surveyed fishers with relatively high household incomes (25%) does not vary significantly across NFI shares.

Moving to the metrics of social and psychological attachment to fisheries, we find that fishers' fisheries-specific social capital strongly declines as the NFI share increases. Similarly, the index of fishery identity also declines with the intensity of non-fishery income activities. The nature and direction of causation is impossible to uncover from these correlations; however, they are consistent with the hypothesis that fishers with weaker personal and social attachment to fisheries are more likely to pursue livelihood diversification opportunities outside fisheries, and therefore find it more difficult to invest in fishery-specific social capital. Interestingly, the relationship between NFI share and job satisfaction depends on whether monetary or non-monetary aspects of satisfaction are considered. Satisfaction with nonmonetary aspects of fishing as a job has no relationship with NFI share, whereas satisfaction with the monetary (livelihood) aspect of fishing is significantly lower for fishers with a high NFI share. Although we cannot establish causality, this finding is consistent with the hypothesis that fishers diversify their livelihoods more highly on the basis of pecuniary factors as opposed to dissatisfaction with non-monetary aspects of fishing.

There are several clear and intuitive trends illustrating the tradeoffs in effort spent earning fisheries vs. non-fisheries income. We find that West-Coast fishers in the high NFI share group employ fewer crew members, work fewer fishing days, earn less average fishing revenue, and are subject to higher within-fishery financial risk. These differences are all statistically significant and uniformly trending across the zero, low, and high NFI share groups – suggesting that fisheries and non-fisheries income function as substitutes in a gross time-allocation sense.

Similarly, we find that high NFI share fishers have a lower diversity of within-fishery revenue earned across species, space, and time relative to fishers that only work in fisheries. This pattern is present to a lesser, and not always statistically significant, extent for low NFI fishers. Altogether, these patterns suggest that livelihood diversification through NFI tends to come at the cost of greater diversification margins *within* the fishery context.

Table 1: Summary statistics of key variables across groups of non-fish income (NFI) income earners.

| NFI Share group | Zero | Low | High | t-test | t-test |
|---|---|---|---|---|---|
| NFI Share | 0 | 0< & <0.5 | >0.5 | Zero, Low | Zero, High |
| | (n = 610) | (n = 274) | (n = 346) | | |
| Social capital | $\mu$ = 0.17 | -0.02 | -0.34 | p=0.007*** | p<0.001*** |
| | $\sigma$ = 0.98 | 1.00 | 0.87 | | |
| Identity | $\mu$ = 0.14 | 0.01 | -0.23 | p=0.088* | p<0.001*** |
| | $\sigma$ = 0.96 | 1.00 | 1.00 | | |
| Job quality | $\mu$ = 0.04 | 0.11 | -0.04 | p=0.345 | p=0.215 |
| | $\sigma$ = 0.98 | 0.97 | 0.98 | | |
| Job livelihood | $\mu$ = 0.14 | 0.07 | -0.22 | p=0.329 | p<0.001*** |
| | $\sigma$ = 0.96 | 1.03 | 1.00 | | |
| n household members | $\mu$ = 2.54 | 2.57 | 2.49 | p=0.698 | p=0.598 |
| | $\sigma$ = 1.24 | 1.18 | 1.17 | | |
| Age | $\mu$ = 55.09 | 53.85 | 54.81 | p=0.195 | p=0.750 |
| | $\sigma$ = 12.81 | 13.08 | 12.49 | | |
| n crew members employed | $\mu$ = 2.27 | 2.01 | 1.38 | p=0.010** | p<0.001*** |
| | $\sigma$ = 1.37 | 1.29 | 1.19 | | |
| Total effort days | $\mu$ = 32.99 | 28.78 | 15.10 | p=0.033** | p<0.001*** |
| | $\sigma$ = 30.07 | 25.49 | 15.69 | | |
| Total Revenue (10,000 USD) | $\mu$ = 12.52 | 7.59 | 1.85 | p<0.001*** | p<0.001*** |
| | $\sigma$ = 19.31 | 17.04 | 6.74 | | |
| Within-fisheries risk (CV) | $\mu$ = 0.42 | 0.47 | 0.58 | p=0.020** | p<0.001*** |
| | $\sigma$ = 0.25 | 0.29 | 0.33 | | |
| Space diversity | $\mu$ = 1.55 | 1.37 | 1.21 | p<0.001*** | p<0.001*** |
| | $\sigma$ = 0.81 | 0.63 | 0.49 | | |
| Species diversity | $\mu$ = 1.57 | 1.49 | 1.43 | p=0.110 | p=0.001*** |
| | $\sigma$ = 0.67 | 0.71 | 0.60 | | |
| Time diversity | $\mu$ = 13.44 | 12.36 | 7.66 | p=0.092* | p<0.001*** |
| | $\sigma$ = 9.49 | 8.37 | 6.25 | | |
| Household income < 50K | $\mu$ = 0.24 | 0.31 | 0.22 | p=0.028** | p=0.522 |
| | $\sigma$ = 0.43 | 0.46 | 0.41 | | |
| 50K < Household income < 125K | $\mu$ = 0.46 | 0.44 | 0.51 | p=0.696 | p=0.097* |
| | $\sigma$ = 0.50 | 0.50 | 0.50 | | |
| 125K > Household income | $\mu$ = 0.25 | 0.22 | 0.24 | p=0.306 | p=0.624 |
| | $\sigma$ = 0.44 | 0.42 | 0.43 | | |

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

### 4.2.2. Model of earning NFI> 0

The linear probability model coefficients in Table 2 are the estimated change in probability of a West Coast fisher earning any NFI for a one-unit change in the independent variables. The specifications increase in completeness from left to right. Model 1 focuses on fisher specific demographic and social-psychological variables. Model 2 adds measures of effort, crew employment and fisheries financial risk (CV), whereas models 3 and 4 add metrics of space, species, and time diversity. Models 1-3 control for spatial gradients in NF employment through state fixed effects, while Model 4 utilizes county fixed effects instead. Unless otherwise indicated, our description of results corresponds to Model 4.

Neither age nor household size are associated with NFI earnings. Examining the social psychological variables, we find that stronger fishing-related identity is consistently associated with statistically significant reductions in the incidence of NFI; a 1 standard deviation ($\sigma$) increase in the identity index reduces the probability of NFI by 0.057. We find a similar decrease in the probability of earning any NFI of $0.052/\sigma$ for job livelihood satisfaction, whereas job quality satisfaction, apart from livelihood considerations, is positively associated with the propensity toward earning NFI ($0.062/\sigma$). Social capital, while significant and negative in model 1, falls in magnitude and significance upon adding additional controls.

Turning to the influence of fishery-specific decisions and risk, we find that the probability of pursuing NFI decreases by 0.062 for 1 SD increase in crew members employed, which is qualitatively robust and significant across specifications. Earning NFI appears positively related to fisheries risk and negatively related to total effort in model 2. However, these estimates attenuate to statistically insignificant levels after controlling for within-fisheries diversity metrics.

Our estimates show that not all within-fishery diversification has the same association with the tendency to seek outside employment. Indeed, species diversification, the most frequently discussed mechanism for fishery diversification, has no statistically significant or empirically meaningful partial correlation with the tendency to earn NFI. However, increases in spatial and temporal diversity within West Coast fisheries are significantly associated with a reduced tendency toward diversification outside of the fishery through NFI (reductions of $0.053/\sigma$ and $0.067/\sigma$, respectively).

Table 2: Predicting positive NF income.

| | NF income earner: 1 = Yes, 0 = No | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| Social capital | −0.059*** | −0.028 | −0.035* | −0.025 |
| | (0.017) | (0.018) | (0.019) | (0.020) |
| Identity | −0.050*** | −0.049*** | −0.062*** | −0.057*** |
| | (0.017) | (0.018) | (0.018) | (0.018) |
| Job quality | 0.073*** | 0.061*** | 0.068*** | 0.062*** |
| | (0.019) | (0.020) | (0.020) | (0.021) |
| Job livelihood | −0.072*** | −0.049** | −0.050** | −0.052** |
| | (0.017) | (0.019) | (0.020) | (0.020) |
| n household members | 0.000 | 0.017 | 0.020 | 0.018 |
| | (0.015) | (0.016) | (0.016) | (0.016) |
| Age | −0.002 | −0.007 | −0.016 | −0.013 |
| | (0.015) | (0.016) | (0.016) | (0.016) |
| Within-fisheries risk | | 0.040** | 0.020 | 0.011 |
| | | (0.016) | (0.017) | (0.017) |
| n crew members employed | | −0.091*** | −0.080*** | −0.062*** |
| | | (0.018) | (0.018) | (0.019) |
| Total effort days | | −0.083*** | −0.037 | −0.022 |
| | | (0.015) | (0.025) | (0.028) |
| Space diversity | | | −0.061*** | −0.053*** |
| | | | (0.015) | (0.017) |
| Species diversity | | | −0.017 | −0.011 |
| | | | (0.017) | (0.018) |
| Time diversity | | | −0.057** | −0.067** |
| | | | (0.027) | (0.029) |
| State FE | Yes | Yes | Yes | No |
| County FE | No | No | No | Yes |
| $R^2$ | 0.072 | 0.131 | 0.159 | 0.245 |
| Adj. $R^2$ | 0.060 | 0.116 | 0.141 | 0.168 |
| Num. obs. | 1192 | 1034 | 981 | 981 |

***p < 0.01; **p < 0.05; *p < 0.1

### 4.2.3. Model of NFI income share, conditional on NFI> 0

We find that fewer variables are significant predictors of the NFI magnitude than of the decision of whether to earn NFI or not (Table 3). Interestingly, some variables that were insignificant as explanatory variables for positive NFI are significant predictors of NFI share. For example, whereas age was insignificant as a predictor of positive NFI, we find that a 1 standard deviation increase in age increases the share of NFI by 0.042 in the most complete model. The social-psychological variables that were previously important for explaining positive NFI (identity, job quality satisfaction, job livelihood satisfaction) are statistically zero. However, we find that increases in social capital are significantly associated with reductions in NFI share by $0.042/\sigma$, conditional on earning any NFI at all.

Variables related to fishery-specific decisions and risk exhibit similar patterns of magnitude and significance as in Table 2. As with the model of NFI incidence, we find that the number of crew members has a strong negative relationship with NFI share (reduction of $0.082/\sigma$), while both effort days and fisheries-specific risk attenuate in magnitude and become insignificant once diversification measures our included in the model.

Both spatial and species diversity are highly insignificant in their relationship with NFI share. Temporal diversity, on the other hand, has a significant and similarly-sized association with NFI share as it does on NFI incidence, with a 1 standard deviation increase in temporal diversity resulting in a 0.069 reduction in the share of NFI income.

Table 3: Predicting the proportion of NF income earned, conditional on earning any NFI.

| | NF income as proportion of total income | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| Social capital | −0.063*** | −0.046*** | −0.054*** | −0.042** |
| | (0.015) | (0.016) | (0.017) | (0.019) |
| Identity | −0.025 | −0.005 | −0.009 | −0.014 |
| | (0.017) | (0.016) | (0.017) | (0.019) |
| Job quality | −0.001 | −0.013 | −0.011 | −0.011 |
| | (0.019) | (0.020) | (0.021) | (0.022) |
| Job livelihood | −0.045*** | −0.015 | −0.008 | −0.002 |
| | (0.017) | (0.018) | (0.019) | (0.021) |
| n household members | −0.010 | 0.022 | 0.016 | 0.022 |
| | (0.014) | (0.015) | (0.016) | (0.017) |
| Age | 0.032** | 0.042*** | 0.036** | 0.042** |
| | (0.014) | (0.015) | (0.016) | (0.017) |
| Within-fisheries risk | | 0.026* | 0.017 | 0.023 |
| | | (0.014) | (0.015) | (0.015) |
| n crew members employed | | −0.070*** | −0.061*** | −0.082*** |
| | | (0.015) | (0.017) | (0.019) |
| Total effort days | | −0.091*** | −0.044** | −0.046* |
| | | (0.014) | (0.019) | (0.026) |
| Space diversity | | | −0.005 | 0.002 |
| | | | (0.014) | (0.020) |
| Species diversity | | | 0.005 | 0.000 |
| | | | (0.017) | (0.018) |
| Time diversity | | | −0.061*** | −0.069** |
| | | | (0.022) | (0.028) |
| State FE | Yes | Yes | Yes | No |
| County FE | No | No | No | Yes |
| $R^2$ | 0.117 | 0.230 | 0.231 | 0.373 |
| Adj. $R^2$ | 0.098 | 0.206 | 0.200 | 0.241 |
| Num. obs. | 596 | 494 | 466 | 466 |
| RMSE | 0.326 | 0.301 | 0.302 | 0.294 |

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

### 4.2.4. Unexplained spatial patterns in NFI

Figure 5 plots the de-meaned county fixed effects for both the NFI incidence (Table 2) and intensity (Table 3) models. Together these figures show spatial patterns in the tendency and intensity of NF income that are not directly captured by model covariates. There is patchiness in the probability of NFI, with the probability being lower than otherwise predicted in much of Washington state but higher in inland parts of the Bay Area in Northern California and much of Western Oregon. The pattern of fixed effects for the NFI intensity model follow a similar pattern to the NFI incidence plot but are more strongly positive in non-coastal counties in Northern California and Oregon. Many of the areas with higher NFI incidence and intensity are in urban or suburban areas with significant potential sources of non-fishing employment. They are also areas where the cost of living is comparatively high, perhaps leading to increased pressure for NFI on the part of fishers. We note that fixed effects for most coastal counties in both specifications, where much of the sample resides (Figure S.2), are near zero suggesting that the model predicts NFI well in these areas.

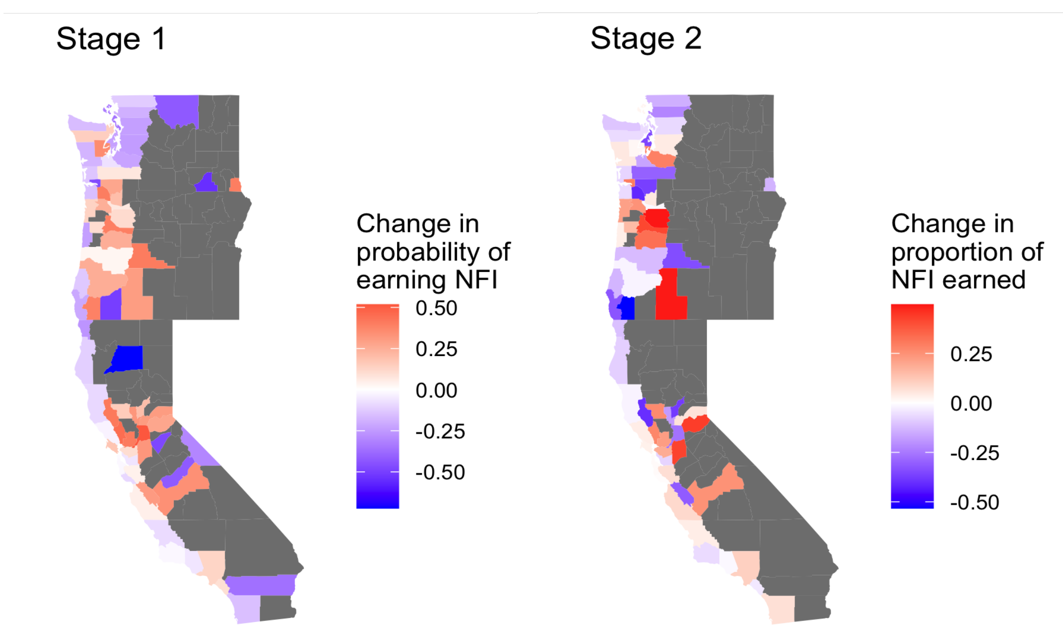


Figure 5: Mapping of the county level fixed effects from model run 4 for our stage 1 (left) and stage 2 (right) regression models.

# 5. Discussion & Conclusion

This study provides a rare analysis of the drivers and importance of fishers' livelihood diversification. Based on the results of the 2017 West Coast fishers' survey, we find that over 50% of fishers in this sample are earning personal income from non-fishing occupations, with nearly 30% deriving more than half of their personal income from non-fishery sources. As such, NFI may play a critical role in sustaining households and fishing communities. Therefore, understanding the correlates of NF employment and income, as well as the patterning of NFI dependence over geography, fisheries species, and seasons of the year is important for revealing the ongoing functions provided by NFI in fishing communities and how these roles may change with alterations to fishery management policies or climate or oceanographic shocks.

On the whole, our study does suggest that diversifying household income through NFI tends to be an alternative to greater fishery effort and to enhanced within-fishery diversification. In particular, spreading a fixed amount of fishing activity across the year or across counties of landing makes an individual less likely to earn NFI, while taking more trips and spreading this effort over more weeks of the year tends to reduce the share of NFI in the income contributed by a fisher. Therefore, fishery diversification and NFI tend to operate as substitutes. Nevertheless, the relatively low intensity of many West Coast commercial fishers' fishery employment is such that periods of high NF employment and high fishery revenues do not consistently move counter to one another and may even coincide for many NF occupational categories (Fig. 4).

We find some evidence that the extent to which fishery intensification and diversification are substitutes vs. complements with NFI may be mediated based upon the source of NFI itself. In particular, the relatively small minority of fishers with NFI deriving from "management" sources earn a disproportionate share of fisheries revenues relative to other NF occupational categories, suggesting that the greater flexibility of many jobs in this category, as well as non-labor income from capital ownership, may weaken the substitute relationship between fishing and NF income. This does not appear to the case, however, for the more common but less flexible and labor-driven sources of NFI such as construction.

Assessing geographic patterns of NFI may be important for understanding community fishery dependence. The degree of community fishery dependence has generally been assessed on the basis of total or per capita revenues, but this metric fails to account for other income sources that may make fishers less fishery-dependent (Norman et al., 2022). Considering NFI, we find that fishers located in rural or coastal areas, particularly in Washington state, have lower presence and shares of NFI. This is perhaps due to fewer desirable outside employment opportunities in the region, which is consistent with our hypothesis that higher opportunity costs of not fishing would be associated with a lower incidence and intensity of earning income from NF occupations.

Norman et al. (2022) also found that fishers from communities with strong ties to fishing also tend to have higher dependence on fishing income at the household level and in terms of personal contributions. Communities with high reliance (higher per-capita fishery income) tend to have higher levels of social capital and identity tied to fishing and lower average proportions of NFI (Norman et al., 2022). Our results confirm these patterns at the individual level, as was hypothesized, though with some interesting nuances. We find that fishers with high social capital related to fishing tend to have lower proportions of income from non-fishery sources but are not significantly less likely to have NFI at all. A stronger identity related to fishing does tend to reduce the likelihood of having NFI but not the proportion of personal income from NFI.

Job satisfaction related to income from fishing is correlated negatively with the likelihood of earning any NFI, but counter to what we hypothesized, the opposite is true of non-monetary fishery job satisfaction. This may be explained by NFI earners placing more weight on particular non-pecuniary aspects of fishing (e.g., “adventure” or “being on the water”) relative to those whose personal income is entirely from fishing. We also find evidence against our hypothesis about younger fishers being associated with a higher non-fishing share, conditional on earning any NFI, which may reflect older NFI earners allocating more effort to less physically intense occupations than fishing. Fishers with more crew are themselves less likely to have NFI, as well as having a smaller non-fishing share of income. This suggests that vessel owners on which other fishers rely may be particularly dependent on fisheries, creating a potentially greater vulnerability. However, this vulnerability may be partially mitigated by greater within-fishery diversification; as previously noted, fishers with high diversification of fishing income tend to be less reliant on NFI.

Our analysis shows that fishers with greater NFI may exhibit distinct patterns of species dependency relative to fishing specialists. Some fisheries such as salmon and lobster appear to be more important to part-time fishers, while others, such as Dungeness crab, are more heavily favored by full-time fishers. These patterns may result because of complementarities in these species' seasons with NF employment or due to relatively low capital requirements that are amenable for part-time fishers. Alternatively, causation may be reversed, such that fishers pursuing particularly risky fisheries (e.g., salmon) may highly value the risk reduction associated with NF employment. Understanding the links between NFI and fishery dependence can help fishery managers craft regulations to limit impacts in some cases and at least be aware of them in others so that communities can better prepare. Similarly, knowledge of what non-fishery sectors non-fishing households derive income from and what fisheries they participate in could prove useful to fishery managers. For example, a downturn in construction may lead to more participation in a fishery in which many participants also work construction.

While fishery managers may be particularly concerned with avoiding negative impacts on communities or fishery sectors that are more dependent on fishing income, fishers that complement fishing income at certain times of year with NFI could potentially be sensitive to regulations or events that shift the timing of fisheries. Many fisheries are seasonal either because of the phenology of the species or because they are run as derbies. Individuals with NFI may be sensitive to shifts in timing (e.g., fishery closures) if they have seasonal jobs that complement their fisheries participation. Further, those earning higher levels of NFI may have less flexibility to voice these concerns through demanding fisheries management processes (e.g., in-person PFMC meetings).

While our analysis provides useful insight on the role of NFI for fishers, it does suffer from some shortcomings as a result of its focus on a single (albeit expansive) region as well as the brevity and cross-sectional nature of the 2017 survey. Due to the lack of repeated observations on NFI, and because we lack data on the overall variability of household incomes, as opposed to the fishery component of revenues from fish ticket data, we cannot empirically assess how NFI on the part of fishers affects the overall level and variability of household incomes. Future research should endeavor to gather longitudinal data on both within-fishery and livelihood diversification while also measuring household-level livelihood variables. In addition, researchers should move beyond understanding the NFI of fishers alone – instead placing this income and employment in the overall context of livelihood activities within the broader household, including spousal and dependent employment. Finally, understanding the interactions of NF employment and income would be facilitated by the collection of qualitative data from fishers on the specific ways in which their fishing and non-fishing activities interact.

# Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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# Author Contributions

All authors conceived and planned the study. JA and DH provided the data sources. TT led model development and data analysis with support from JA. All authors contributed to writing of the manuscript.

## Data Availability Statement

The landings data and vessel registration data utilized for this study are confidential fisheries data and cannot be shared by the authors. They can be obtained through PacFIN https://pacfin.psmfc.org/home/ upon completion of a data non-disclosure agreement. Data from the 2017 fisheries participation survey are also confidential and cannot be shared by the authors. Summary results by state and county are available online at https://www.fisheries.noaa.gov/national/west-coast-fisheries-participation-survey-results. Individual level data can be obtained subject to a data access agreement with NOAA, Northwest Fisheries Science Center (contact dan.holland@noaa.gov).

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# Supplemental Tables

| Sample SOC crosswalk | | |
|---|---|---|
| SOC Code | SOC Title | Sample open ended responses |
| 47-0000 | Construction and Extraction Occupations (n = 127) | “Construction”, “Carpentry”, “Builder”, “Handyman”, “Plumbing”, “Electrician”. |
| 53-0000 | Transportation and Material Moving Occupations (n = 66) | “Trucking”, “Driver”, “Pilot”, “Boat captain” , “Warehouse”, “Boat operator”. |
| 11-0000 | Management Occupations (n = 63) | “Rental income”, “Rentals”, “Ran farmers market”, “Built websites”, “Own a fishing lodge”, “Own a hotel”, “Restaurant owner”. |
| 45-0000 | Farming, Fishing, and Forestry Occupations (n = 61) | ”Farming”, “Forester”, “Timber”, “Logging”, “Sport fishing”, “Fishing rod building”, “Agriculture”, “Aquaculture”, “Fish and wildlife conservation”. |
| All others. | Other (n = 259) | “Real estate”, “Sales”, “Teacher”, “Barber”, “Firefighter”, “Radiology”, “General contractor”. |

Table S.1: Examples of open-ended survey responses and our associated SOC occupation codings.

# Supplemental Figures

**29.** Over the last 3 – 4 years: what percentage of the income you personally contributed to your household was from work other than commercial fishing? __________%

**30**. If more than 0% in question 29, what type of non-fishing work did you do in this period?

________________________________________

________________________________________

**31.** In recent years how often do you personally earn non-fishing income in each quarter?

**January-March**

- ❑ Always
- ❑ Mostly
- ❑ Sometimes
- ❑ Never

**April-June**

- ❑ Always
- ❑ Mostly
- ❑ Sometimes
- ❑ Never

**July-September**

- ❑ Always
- ❑ Mostly
- ❑ Sometimes
- ❑ Never

**October-December**

- ❑ Always
- ❑ Mostly
- ❑ Sometimes
- ❑ Never

Figure S.1: Key NFI related survey questions.

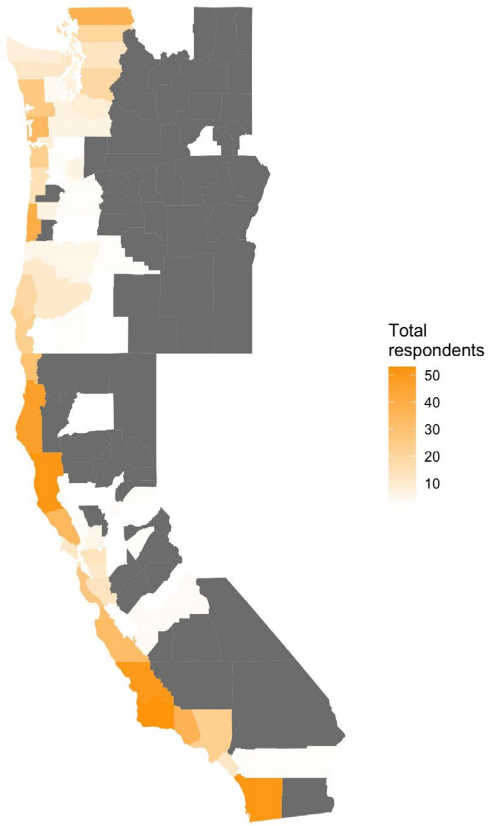


Figure S.2: Mapping of the total number of respondents in each county in California, Washington, and Oregon from our sub-sample used in model 4 of our stage 1 regression (n = 981).