Fishing Portfolio Response to a Climate Shock

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Abstract

Fishing portfolio diversification has been identified as a mechanism to mitigate risk exposure for harvesters operating in wild-capture fisheries. As in financial markets, however, the benefits from diversification in fisheries will be a function of whether individuals adopt active or passive investment strategies. There is a long history of evidence of the superior performance of passive investment strategies in the financial economics literature, but little is known about the relative performance of these two strategies in fisheries. Here we use a case study of an observed and high-profile climate shock in the California Dungeness crab fishery to estimate the impact of a relatively active investment strategy, in the form of an extreme decision to exit the fishery for the season, in response to the shock. We find robust evidence of negative revenue impacts from an active investment strategy in this context.

Keywords

Fishing portfolio, diversification, Dungeness crab, harmful algal blooms, climate change

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Fishing is a risky business. Harvesters, operating in wild-capture fisheries, depend on natural production and are thus subject to environmental, biological/ecological, and market shocks and, for fisheries without well-defined property rights, shocks to resource competition [Kasperski and Holland, 2013, Kroetz et al., 2019]. Diversification is a mechanism that can mitigate exposure to risk when the returns to assets in a fishing portfolio vary asynchronously. If diversification does, in fact, buffer harvesters from risk, it is something that managers should consider both when designing policies to promote the resilience of fishing communities, e.g., to climate change, and when implementing policies that affect the opportunities for diversification such as adopting limited entry programs or ITQs.

The literature provides some empirical support for the idea that diversification across species and/or fisheries yields risk-mitigating benefits in fisheries at multiple scales. Kasperski and Holland [2013] examine harvester portfolios for vessels active in the U.S. West Coast and Alaskan fisheries, finding what they call a "dome-shaped" relationship between diversification and the coefficient of variation in fishing revenues, i.e., small amounts of diversification are associated with an increase in the variability of fishing revenues, but further diversification is associated with reductions in the variability of fishing revenue, as expected. Cline et al. [2017] examine diversification at the level of Alaskan fishing communities, defined by census area, finding that diversified communities were protected from a regime shift, starting in 1989, characterized by changes in productivity and species composition and low market prices for wild salmon due to increases in salmon produced by aquaculture. Dee et al. [2016] explore functional diversification at the level of an ocean region, measured as the degree to which an ocean region has catches spread across species with different temperature preferences, finding that functional diversity buffers the impacts of climate variability on the total tons harvested.

More recent literature focuses on the importance of diversification over multiple dimensions including diversifying over species, space, and time [Abbott et al., 2023]. For example, O'Farrell et al. [2019] use a natural experiment, created by an exogenous fishery closure in the longline fishery in the US Gulf of Mexico, to explore the relative performance of an exploratory fishing strategy where vessels invested in diversifying fishing efforts over various fishing locations to an exploitative strategy where fishing effort was concentrated in space. The authors find transitory payoffs to diversifying efforts over space during the fishery closure.

As in financial markets, however, the benefits from diversification in fisheries will be a function of whether an individual adopts an active or passive investment strategy. As discussed in Abbott et al. [2023], to employ a passive strategy to diversification, harvesters can allocate an identical amount of fishing effort to each fishery in their portfolio season after season.

There is a long history of evidence of the superior performance of passive investment strategies in the financial economics literature [Tobin, 1958, Fama, 1970, Samuelson, 1974, Malkiel, 2003]. More recently, added support for passive investing comes from research in behavioral finance showing strong evidence that individual investors are susceptible to "overconfidence", which can lead to "excessive trading", i.e. trading too frequently and at a loss. Overconfidence is simply described as a scenario where investors believe too strongly in their mistaken estimates, causing them to overreact to the information feeding into those estimates. In an early study testing the overconfidence hypothesis Odean [1999] finds that the average returns to securities purchased is less than those to securities sold after 84, 252, and 504 trading days. The result is stable after adjusting for trades due to liquidity constraints and risk rebalancing [Odean, 1999]. Moreover, losses are greater for the most active traders [Odean, 1999].

Importantly, overconfidence has been shown to affect financial experts who, like fisheries harvesters, have large stakes in their performance. For example, Ben-David et al. [2013] survey senior financial executives, collecting their quarterly estimates of the mean 1- and 10-year return of the S&P 500, along with estimated 80% confidence intervals, finding that estimates rarely fall into provided confidence intervals (only 36.3% of the time) and that the actual variability in returns to the S&P 500 were significantly greater than investors estimated.

However, whether passive investment strategies are beneficial in fisheries is an open question. On one hand, diversification through active investment strategies may be beneficial if harvesters are able to make accurate predictions of the financial returns to effort in all fisheries available to them and adjust their effort accordingly [Abbott et al., 2023]. On the other hand, in some cases harvesters will lack the information needed to make accurate predictions of the financial gains from a portfolio shift. This may be particularly true with climate-driven shocks that are unprecedented in nature.

To our knowledge, previous work related to the revenue impacts of active approaches to diversification entirely consist of correlational analyses where fishing portfolio changes, defined as shifts in the distribution of revenue across fisheries or stocks in a portfolio, are correlated with fishing returns. Results from these correlational analyses are mixed. For example, using data on Alaskan fishing communities, Cline et al. [2017] find that portfolio changes are positively correlated with increases in total fishing revenue. In contrast, using individual data, Anderson et al. [2017] find that shifting portfolios towards greater specialization is correlated with increases in fishing revenue and shifting portfolios towards greater generalization is associated with decreasing fishing revenues.

These analyses cannot uncover the relative performance of an active versus passive approach to diversification for two reasons. First, because of how portfolios are defined in these studies, exogenous fisheries shocks, e.g. to biomass or prices, will drive portfolio shifts even with a constant level of effort devoted to each stock. Therefore, shifts in revenue distributions across fisheries or stocks are not a good metric of active portfolio strategies.

Second, correlational analyses suffer from omitted variables bias when fisheries shocks, e.g., to biomass or prices, are unobserved, because diversification is endogenous to these shocks. For example, a negative shock to a fishery may drive an individual to participate in more fisheries to make up for revenue losses, shifting their portfolio towards greater diversification. That same shock may also drive decreases in revenue. In this case, the unobserved shock would lead to a negative relationship between diversification and fishing revenue, but that relationship would not be causal.

Here we contribute to the literature by exploring the causal impact of an active approach to diversification in fisheries focusing on diversification over fisheries, defined as the combination of species and region (rather than, e.g. diversification over timing of harvest). We consider the case study of the 2014-2016 Northeast Pacific Marine Heatwave, which led to a harmful algal bloom (HAB) contaminating Dungeness crab along the West Coast of the United States. Managers in California used fisheries closures to control human health risks. The closures lasted about 4.5 months and 5.5 months in the Central and Northern districts respectively and were unprecedented in duration and in the impacts they had on harvesters and fishing communities [Ritzman et al., 2018]. Industry wide harvest in California fell by 25% from the previous season and ex-vessel prices were negatively impacted [Mao and Jardine, 2020]. Importantly, the event was known to generate a response from harvesters as some vessels fished other species or in other locations, while other vessels decided to forego earning fishing revenue in other fisheries in order to wait for the California Dungeness crab opening [Fisher et al., 2021, Holland and Leonard, 2020].

We tackle the endogeneity problem by analyzing the impact of this observed and unprecedented shock, i.e. the HAB event, leading to closures, the duration of which was unknown, *ex ante*, to managers and harvesters alike. We argue the lack of information on the duration of the shock, and thus the impacts to revenue from remaining in the California Dungeness crab fishery, drove exogenous variation portfolio shifts which we can use to estimate the impact of relatively an active diversification strategy.

We find evidence of negative revenue impacts from highly active investment strategies in the form of the extreme decision to leave the California Dungeness crab during the HAB season. Our results are insensitive to model specification and robustness checks.

The remainder of this article is organized as follows: We first present background information on our case study. We describe our econometric model, estimators, and robustness checks. We then describe the data, sample, and variables used in our analysis. We present and discuss the results of our analysis. We then conclude.

1 Background

On the U.S. West Coast, Dungeness crab are primarily harvested from their nearshore habitat, or within three nautical miles from the coast. As such, Dungeness crab are managed by the state departments of fish and wildlife in California, Oregon, and Washington. Each state manages its respective fishery by limiting entry and with sex and size restrictions on harvest and seasonal closures to protect molting crab [Porzio, 2015]. Despite limited-entry regulations, the Dungeness crab fisheries are derby fisheries with most of the volume landed within the first 6 weeks of the fishing season.

While limited entry permits allow access to various fishing areas in a given state, each state has designated management areas at a finer spatial scale [see Free et al., 2022, for more detail].[1] For example, the California Dungeness crab fishery is divided into northern and central management districts at the Mendocino-Sonoma County border. Each management district contains several management areas. Management areas in the central district are typically open from November 15th through June 30th and the northern California season runs from December 1st through July 15th. Coastal fisheries in Oregon and Washington commence in December 1st.[2] We hereafter refer to a fishing season that begins in year X and ends in year Y as the Y fishing season.

However, season start dates in all three states can be delayed for a number of reasons including extended price negotiations, weather-related delays, management delays to allow for increases in crab meat content, and delays due to harmful algae blooms. The harmful algae *Pseudo-nitzschia* is of particular importance to the Dungeness crab fishery. *Pseudo-nitzschia* was first detected on the U.S. West Coast in the 1920s, and can produce a neurotoxin called domoic acid, which is harmful to humans and can even cause death. As opportunistic feeders, Dungeness crab can consume *Pseudo-nitzschia* resulting in potentially dangerous levels of domoic acid concentrating in the crab viscera.

Thus, to protect human health, all three states on the U.S. West Coast have integrated domoic acid monitoring with management actions. Specifically, before the season start date, in each management area, state managers collect a sample of six crabs, testing whether domoic acid concentrations in the meat and vicera exceed established thresholds, 20 ppm and 30 ppm respectively. If any of the six crabs exceed the thresholds, the fishing area is delayed until the area passes two consecutive tests taken at least seven days apart [see Free et al., 2022, for more detail].

From 2014 to 2016, the Northeast Pacific Marine Heatwave, also known as "the blob", led to unusually warm sea surface temperatures [McCabe et al., 2016]. Warm waters were coupled with a series of intermittent

[1] Note, however, that the ability to access a fishing area under a state limited-entry permit can be limited by the state's fair start provisions. See Jardine et al. [2020] for more detail on fair start provisions.

[2] The Puget Sound fishery in Washington is open from October to December 31^{st} each year.

moderate upwellings in April and May 2015 providing nutrients to fuel detectable toxic algal blooms [Ryan et al., 2017]. However, some nutrient levels remained much lower than average, particularly silicates which were barely 50% of their long-run mean levels [Ryan et al., 2017], possibly due to a phytoplankton bloom off the Oregon coast in late winter 2015 that was the largest observed in 20 years [Du et al., 2016]. *Pseudo-nitzschia* can survive relatively well in low-silicate conditions and quickly respond to influxes of nutrients occurring during upwellings [McCabe et al., 2016]. Thus, the intermittent nature of the spring upwelling may have likewise provided stronger than normal growth conditions for *Pseudo-nitzschia*, transporting the bloom toward shore while continuing to mix upwelled water [McCabe et al., 2016, Ryan et al., 2017].

Managers, aware of the ocean conditions, began monitoring for domoic acid earlier than usual, detecting elevated levels of domoic acid as expected. Ekstrom et al. [2020] report that early on, a group of harvesters requested that the California Department of Fish and Wildlife uniformly delay the season along the entire California coast to promote equitable impacts across harvesters and to avoid public confusion over whether California crab were safe to eat. Later, when it was clear that the delay would last longer than anticipated, harvesters requested area-based closures to minimize economic losses [Ekstrom et al., 2020].

Regardless of managers' responsiveness to harvesters' requests, interviews conducted by Ritzman et al. [2018] revealed confusion, over the testing process and resulting management actions, and distrust of managers. One factor leading to distrust of managers was the fact that fishing areas in Northern California were closed, while those in Oregon, just north of the border, were open [Ritzman et al., 2018].[3]

Ultimately, the Dungeness crab fishery was delayed for four and a half months in the Central California district and roughly five and a half months in the Northern California district, pushing the California season into the spring, eliminating access to valuable holiday markets, e.g., Thanksgiving, Christmas, New Year, and Chinese New Year [Mao and Jardine, 2020], and conflicting with the timing of other fisheries opening in the spring and summer. The duration of the delays were unprecedented, as previous delays in the California fishery had been on the order of days to weeks. Delays in Dungeness crab fisheries in Oregon and Washington lasted about one month.

Many harvesters active in the California Dungeness crab fishery also participate in other fisheries managed under a variety of approaches ranging from open access (CA pink shrimp caught from Point Conception to the California-Mexico border), to limited entry (CA pink shrimp caught between the California-Oregon border and Point Conception), to catch shares (bottom and midwater groundfish trawl in all three West Coast states).

Thus, California harvesters were faced with the difficult decision of how to respond to the delays. Options

[3] While on the surface, the cross-state differences in delays appeared to be driven by differences in management, monitoring data show that domoic acid concentrations changed sharply at the state border. See Panel B, Figure 2 in Free et al. [2022].

included: (Option # 1) waiting until the California Dungeness crab fishery opened and foregoing earnings in fisheries typically fished after fishing Dungeness crab; (Option # 2) participating in other available fisheries or a non-fishing employment option during the delay period and switching to the California Dungeness crab fishery once open; and (Option # 3) foregoing participation in California Dungeness crab entirely in favor of an alternative fishery or non-fishing employment. Given that Dungeness crab is a high-value fishery and a primary source of income for many U.S. West Coast harvesters [Dewees et al., 2004, Ritzman et al., 2018], and that Dungeness crab is harvested in a derby fishery with the majority of landings occurring in a compressed season, early-season participation is critical to economic success, meaning that many vessels chose Option #1 over Option # 2 [Fisher et al., 2021, Holland and Leonard, 2020]. To our knowledge, there is no qualitative or quantitative analysis of the motivations or outcomes of selecting Option # 3, which we explore here.

2 Empirical Strategy

We explore the revenue impacts of exiting the California Dungeness crab fishery during the HAB season (temporary exit). For those harvesters previously displaying consistent participation in California Dungeness crab and deriving a large fraction of their fishing revenue from California Dungeness crab, the treatment, defined as having exited the California Dungeness crab fishery in the 2016 season to participate in another fishery, represents a large portfolio shift, or a relatively active investment strategy. Although to maintain participation in the California Dungeness crab fishery during the HAB event, the control group may also have had to adjust effort allocations across fisheries in their portfolios, e.g., by foregoing participation in other fisheries, these adjustments were smaller by an order of magnitude (more detail is provided in Section 3). Thus, we consider the large portfolio shifts as the relatively active approach to diversification and the small portfolio shifts as the relatively passive approach to diversification.

To uncover the impacts of a relatively active approach to diversification during the 2016 HAB event, we adopt a difference-in-differences framework. The difference-in-differences framework will identify the average treatment effect on the treated (ATT) as long as three assumptions are met.[4] The three are: (1) no anticipation; (2) the stable unit treatment value assumption (SUTVA); and (3) the parallel trends assumption.

The first and second assumptions, i.e. no anticipation and SUTVA, are not a concern in our analysis. The assumption of no anticipation means that vessels did not adjust their behavior in earlier seasons based on

[4] In earlier work applying the difference-in-differences framework, researchers were more likely to assume that the framework could identify the average treatment effect (ATE), even without randomized treatment, as described in Athey and Imbens [2006]. However, the current literature consistently interprets the difference-in-differences estimator providing an estimate of the ATT conditional on needed assumptions being satisfied [see e.g. Goodman-Bacon, 2021, Cunningham, 2021].

the anticipation of HAB-related closures in 2016. The assumption is not a concern, both because harvesters were unlikely to be able to anticipate the extreme climate shock of 2016, and because, even if they had, there would have been no economic gains from adjustments in the preceding season. Additionally, SUTVA implies that the treatment should not have spillover effects to the control units. We argue that the size of our treatment group, i.e. <10% of our sample, eliminates concern for spillover effects (see Section 3 for more detail about our sample and vessel groups).

However, the parallel trends assumption is a critical and untestable assumption. In our context, the assumption of parallel trends implies that we must assume vessels did not select into treatment based the magnitude of their individual impacts from the HAB event. For example, if those vessels who would have been particularly hard hit by the HAB, had they participated in California Dungeness crab during the event, were the same vessels who chose to exit California Dungeness crab, our estimates would be biased. We argue that the unique and unprecedented nature of the climate shock considered here supports our assumption of parallel trends.

First, harvesters did not have access to forecasts predicting the expected duration of the event, as such forecasting tools do not currently exist. This means that no one knew how long the closures would last, including scientists, managers, and harvesters, and that no one was able to rule out the unlikely outcome of a canceled season. The duration of the closures not only determines the opportunity cost of waiting to participate in the season opener, but also determines market conditions during the season opening, including market prices and the meat content, and thus, value of crabs which begin to molt in the summer. Therefore, individual harvesters would not have had the information needed to formulate accurate estimates of their individual impacts from participating in California Dungeness crab during the HAB season.

Applied to our data, the canonical difference-in-differences model for panel data is as follows:

$$\ln(\text{revenue})_{it} = \gamma_i + \gamma_t + \delta\,(\text{trt} \times \text{post})_{it} + \upsilon_{it}, \tag{1}$$

where $\ln(\text{revenue})_{it}$, the natural log of total fishing revenues from all fisheries earned by vessel i during the crab season t, is a function of a vessel fixed effect (γ_i), a season fixed effect (γ_t), the interaction between an indicator for whether a vessel exited the California Dungeness crab fishery during the HAB season (trt_i) and an indicator variable for the 2016 fishing season (post_t), and an idiosyncratic error term (υ_{it}). Thus, our parameter of interest is δ and represents the average impact of the season exit decision on total fishing revenues for the treatment group.

We acknowledge that covariates may be important to satisfying our parallel trends assumption. Specifically, if the impacts of participating in California Dungeness crab during the HAB season are shaped by vessel characteristics, then it becomes important to control for these characteristics when estimating the impacts of season exit.

First, because Holland and Leonard [2020] show that specialization in California Dungeness crab affected revenue impacts of the HAB event, we include the lagged fraction of total fishing revenue coming from California Dungeness crab as a covariate. Second, because previous research has shown that larger crab vessels tend to have higher mean revenue and more ability to mitigate losses due to environmental shocks [Fisher et al., 2021, Jardine et al., 2020], we include vessel length as a covariate. Third, as the duration of closures varied over space, potential impacts from the HAB event may also have varied over space along with outside opportunities, e.g., more northerly vessels had greater opportunity to fish in the Oregon and Washington Dungeness crab seasons, which did not experience such dramatic season delays. To capture home port, we follow [Holland and Leonard, 2020] and include the lagged mean of revenue-weighted latitude for Dungeness crab trips as a covariate. Finally, vessels with greater historical portfolio diversification may have had more opportunity to diversify away from a fishery that is adversely affected by an environmental shock. Thus, we also include the lagged Shannon diversity index as a covariate.

We use three methods to estimate the δ parameter. First, we explore impact estimates from a two-way fixed effects (TWFE) estimator represented in Equation 1 without the inclusion of covariates. Including covariates in a TWFE model requires several additional assumptions, including that the time-varying covariates are not affected by the treatment [see Payne, 2022, Caetano et al., 2022, for more detail]. In our case covariates such as fishing location and the Shannon index are directly affected by the treatment. Therefore, we exclude covariates from the TWFE model and incorporate them in our two remaining methods, which do not rely on such assumptions.

Our second method is a matched two-way fixed effects approach (MTWFE) which estimates Equation 1 on a matched sample. Specifically, we match each treatment unit to a single control unit using a nearest neighbor matching procedure based on the Mahalanobis distance across the mean of all selected vessel characteristics from the previous two seasons (2014-2015). This procedure more closely approximates a fully blocked randomization than propensity score matching, which maps the data to a single dimension prior to matching treatment and control units [King and Nielsen, 2019].

Results from both Smith and Todd [2005] and Abadie [2005] offer support for integrating matching with the difference-in-differences framework and researchers have applied this coupling in several environmental applications [e.g., Reimer and Haynie, 2018, Ahlfeldt et al., 2019, Blackman and Villalobos, 2021]. Imbens [2015] and Stuart and Rubin [2008] recommend the matching procedure include any variable that researchers believe *a priori* would be associated with both the treatment assignment and outcome. Thus, the goal of matching on these covariates is to reduce imbalances in the joint distribution of potentially confounding pre-treatment covariates when treatment is not randomly assigned [Stuart and Rubin, 2008]. Using matching, the observations in the sample can be restricted or re-weighted so that the observed distributions are similar across treatment assignments, creating treatment and control groups that are more comparable than they would have been without the matching procedure.

Our third method is the newly-developed doubly robust difference-in-differences estimator (DRDID) [Sant'Anna and Zhao, 2020, Callaway and Sant'Anna, 2021]. The estimator essentially combines the approaches integrating covariates through inverse propensity score weighting from Abadie [2005] and integrating covariates through outcome regression from Heckman et al. [1997]. The consistency of difference-in-differences with inverse propensity score weighting depends on the correct specification of the propensity score model and consistency of difference-in-differences with outcome regression depends on the correct specification of the model of control group outcomes. The benefit of the DRDID estimator is that it attains consistency when either model is correctly specified. Note that our DRDID specification integrates all lagged covariate values.

To support our overall approach, we explore evidence of parallel pre-trends empirically using a standard event study analysis. Any violation of parallel pre-trends would suggest our parallel trends assumption is inappropriate. We supplement the event-study analysis with a sensitivity analysis that determines the magnitude of a violation in the parallel trends assumption that would qualitatively change our results.

Additionally, we estimate Equation 1 using alternative definitions of treatment, where treatment is alternatively defined as not participating in the California Dungeness crab opening, or the first few weeks of the season, when the majority of landings occur. Thus, these estimations allow us to understand the impact of a strategy of participating in an alternative fishery while the California Dungeness crab fishery was closed and switching back into California Dungeness crab once it was opened.

Finally, we estimate DID models using the total number of trips as a dependent variable, i.e., the natural log of total trips taken in any fishery for vessel i during the crab season t. While, unlike fishing revenue, it is difficult to compare a trip in the California Dungeness crab fishery to a trip in another fishery, our trip estimates provide a better understanding of whether any estimated changes in revenue correspond to changes in effort, as proxied by the number of fishing trips. A large reduction in trips taken by treated vessels could indicate vessels responded to the shock by increasing labor in the non-fishing sector, earning increased (and unobserved) non-fishing revenue to offset losses in fishing revenue.

3 Data

This section describes our data sources, sample, groups in our sample, and the variables used in exploration and estimation. We also present summary statistics and figures summarizing our data.

3.1 Sources

Our analysis relies on two primary data sources. First, to model vessel-level behavior and outcomes, we utilize confidential vessel-level data on transactions between vessels and processors (fish ticket data). Our fish ticket dataset includes all transactions occurring in California, Oregon, and Washington, during the 2011-2016 fishing seasons, for all vessels that participated in the California Dungeness crab fishery at least once during that time. The data were acquired from the California, Oregon, and Washington departments of Fish and Wildlife and include information on vessel ID, vessel length (in feet), a code for the species landed, volume (in pounds), ex-vessel price (in dollars)[5], and state and fishing port of delivery.

Second, to understand whether vessels participated in a season opening, we utilize a dataset provided by the California Department of Fish and Wildlife, on the 2016 season Dungeness crab opening dates for each California management area.

3.2 Sample

To focus the HAB event, we restrict our analysis to observations occurring during the California Dungeness crab fishing season, which spans November 15th to July 15th, hereafter referred to as "crab season" or "season".

We further restrict our analysis to focus on vessels with consistent participation in California Dungeness crab. Of the 654 vessels that participated in California Dungeness crab during any of the 2012-2016 seasons, our sample includes the 320 vessels that participated in Dungeness crab in each season fished, earning at least \$5,000 in fishing revenue from California Dungeness when participating, earning at least \$5,000 in fishing revenue from any fishery in the 2016 season, and making at least 3 fishing trips in each season fished from 2012-2016.

There are two important things to note about our data. First, although our sample includes vessels participating in Dungeness crab in each season fished, not all these vessels participated in Dungeness crab in each of the 2012-2016 seasons. For example, some vessels enter our dataset after the 2012 season and some vessels are absent from our dataset after entering, e.g., a vessel that participates in 2012 and 2014-2016 but

[5]Ex-vessel prices are adjusted for inflation to represent dollar values in July of 2016 using BLS series CUUR0400SA0.

does not participate in Dungeness crab or any other West Coast fishery in 2013.

Second, although our raw data cover fishing seasons 2011-2016, observations from 2011 are only included in calculating lagged covariate values to be used in the DR approach (as MTWFE only includes covariate values from 2014-2015).

3.3 Groups

We define treated vessels as those that participated in California Dungeness crab in each season fished from 2012-2015, had no earnings in California Dungeness crab in the 2016 season, but earned at least $5,000 and took at least 3 fishing trips in another fishery. There are a total of 22 treated vessels, comprising less than 10 % of our unmatched sample, increasing the plausibility of our SUTVA assumption that control units were not affected by the treatment (Table 1). Based on our sample definition, these 22 treated vessels are those which selected a fishing strategy during the HAB season that had never been selected in previous seasons, representing an extreme portfolio shift or a relatively active approach to diversification.

As a robustness check, we examine alternative definitions of treatment that capture non-participation in the California Dungeness crab opening. Specifically, vessels are considered treated if they participated in California Dungeness crab in each season fished from 2012-2015, participated in California Dungeness crab in the first X weeks of the 2015 fishing season, but not in the first X weeks of the 2016 California Dungeness crab season, and earned at least $5,000 and took at least 3 fishing trips in another fishery over the course of the 2016 season. In our alternative definition of treatment, X represents our definition of the season opening period. Because the 2016 season open dates vary across ports, for each fish ticket we determine whether the landing date is within X weeks of the port opening date. We then determine whether a vessel had California Dungeness crab landings in any of the port opening periods. We explore X values of 2, 4, and 6, resulting in 34, 28, and 25 vessels included in these alternative treatment definitions, respectively.

3.4 Variables

Our key outcome variable is total fishing revenue earned in California, Oregon, and Washington, for each of the crab seasons of 2012-2016. We also explore models using trip count as the dependent variable. Table 1 summarizes variables used in our analysis.

To calculate total fishing revenue, we first filter our fish ticket data to exclude non-commercial catch, discards, tickets without a vessel ID number, tickets outside of the 2011-2016 fishing seasons, and tickets for vessels that did not participate in the California Dungeness crab fishery at least once during the 2012-2016 seasons. We are left with 117,444 fish tickets.

We then adjust potential entry errors in ex-vessel prices by replacing prices with their species/season means if prices are recorded as zero or as more than 4 standard deviations from the species/season means. After adjusting prices, we calculate ex-vessel revenue, for each species on each fish ticket, by multiplying per-pound price by pounds landed. Tickets with entry errors account for a small fraction of state landings, i.e., 0.02%, 0.08%, and 0.05% of total pounds landed in California, Oregon, and Washington respectively. We then drop the 11 observations where ex-vessel revenue is zero (because landed pounds is recorded as zero). We then filter the fish ticket data for vessels in our sample (320 versus 654) before summing ex-vessel revenue for each vessel and season. In this way, our price corrections utilize information from all 654 vessels in our data.

To calculate a Shannon index of diversity, a key covariate, we first assign a "fishery" to all landings in the fish ticket dataset based on species, gear, and state of delivery. Specifically, we define fisheries according to a métier analysis modifying methods from Fuller et al. [2017] and Fisher et al. [2021]. In summary, we define fisheries by identifying clusters of fishing trips with similar catch, gear, and location combinations where the locations we consider are California and other states (Oregon and Washington combined). In total we identify 29 unique métier fisheries. Our Shannon index is then defined as the distribution of fishing revenues across each of the 29 métier fisheries identified in our data. See the Appendix for more detail.

Figure 1 shows the distribution of fishing revenues, across weeks in each of the 2012-2016 fishing seasons, for the métier fisheries that account for at least 1% of fishing revenue earned by vessels in our sample during the crab season. The shaded region of each seasonal plot represents the time span for which at least 90% of the revenue for the California Dungeness Crab fishery was generated. The figure shows, in a typical season, many vessels in our sample participate in other fisheries after participating in the peak California Dungeness crab season. In the 2016 season, these patterns are at least partially preserved although we observe participation in alternative fisheries during the delay.

3.5 Summary Statistics

Panel A of Table 2 presents summary statistics from our data grouped by period and treatment status, for our unmatched sample. The panel shows that vessels in our treated group reduced the share of California Dungeness crab in their portfolios by 68 percentage points, on average. The control vessels, on average, increased the share of California Dungeness crab in their portfolios by 5 percentage points (going from a fraction of 0.87 before the HAB to 0.92 during the HAB season). Thus, there is an order of magnitude difference in the size of portfolio shifts between the two groups. We consider the large portfolio shifts to be the relatively active investment strategy.

Panel A of Table 2 also shows that, prior to the HAB event, the vessels choosing to exit the California Dungeness crab fishery during the HAB event were, on average: less specialized in California Dungeness crab, with 68% of total fishing revenue during the crab season coming from California Dungeness compared to 87%; larger vessels, or roughly 44 feet in length compared to 41 feet; and more diversified as captured by the higher Shannon index of diversification, or an index of 0.54 compared to 0.28. Differences in pre-period means for each of these covariates is statistically significant at the 1% level.

From panel A of Table 2 we also see some similarities between pre-period characteristics in our unmatched sample. Specifically, both the control and treated vessels generate a similar level of total fishing revenue during a crab season (about $250,000 for the treated vessels), land harvest between weeks three and four of the season[6], and take a similar number of trips during the season (about 30 trips for the treatment vessels). None of the pre-period differences in means for these characteristics are statistically significant at the 10% levels.

Finally, Panel A of Table 2 suggests that treatment vessels fared worse during the HAB event with mean total fishing revenues averaging $110,000 versus $130,000 for the control group. From the table we see that most treated vessels did not harvest Dungeness crab in any state, although 5 vessels did land Dungeness crab in OR or WA (crab location is only recorded for 5 treated vessels in the post period).

Unsurprisingly, we find that treated vessels commenced fishing earlier than control vessels, with a recorded landing about 13 weeks into a typical season versus 19 weeks (Panel A of Table 2). Panel A of Figure 2 further explores the distribution of landings across time for vessels in each group for the unmatched sample. The figure shows a large fraction of the treated vessels had recorded landings between 10 and 15 weeks into a typical season whereas the highest density of control vessels had recorded landings between 20 and 25 weeks into a typical season. Thus, we observe a majority of control vessels, in our sample, waiting out the delay as described in [Holland and Leonard, 2020].

Finally, we note that, in the post period, treated vessels took fewer trips on average, or about 14 trips compared to about 17 trips (Panel A of Table 2). Panel A of Figure 3 shows that, while larger number of vessels in the treatment group recorded between 3-5 trips (with 3 trips being our cutoff for inclusion in the sample), many treated vessels took the same number or more trips than our control units. This is important for our analysis, as our goal is to remove vessels that dropped out of fishing entirely during the HAB event and may have found non-fishing employment. We discuss Panel B of Table 2 and figures 2- 3 in Section 4. We also more formally investigate whether the treatment had an impact on total trips using the DID framework, the results of which are discussed in Section 4.

[6]The week of November 15^{th} marks week one of the season and is when the central management area of California is typically open for fishing.

4 Results

Our matching algorithm was largely successful at reducing covariate differences assumed to be correlated with either treatment status or fishing revenue in the 2016 season. Specifically, after matching, these differences are no longer significant with the exception of the difference in specialization which is significant at the 10% level (Table 2).

Panel B of Figure 2 shows that a higher proportion of control units in our matched sample fished before California Dungeness crab was open, with landings in the fish ticket data less than 15 weeks into a typical season. Panel B of Figure 3 shows our matching algorithm, while not using information on the number of trips taken, selected control units that were arguably more similar to our treated units in terms of total trips taken in 2016, by filtering out units with greater than 50 trips.

Figure 4 shows trends in our outcome variable over time for both the matched control and treatment groups. As in Table 2 we see that, on average, treated vessels generate higher fishing revenues than do our control units. Additionally, Figure 4 suggests that the earning differential is relatively stable over time in the pre-period, providing empirical evidence in support of our key identifying assumption. This observation is further supported by results from the event study, which check for statistically significant trend differentials in the pre-period (Panel A of Figure 5). However, because event studies can fail to detect violations of parallel pre-trends, e.g., due to issues of low power [Roth, 2022], we explore the robustness of the statistical significance of our TWFE and MTWFE results to violations of the parallel trends assumption based on methods developed Rambachan and Roth [2023]. We find that our results are robust to allowing for violations of parallel trends up to 1.75 times as big as the maximum violation in the pre-treatment period. See the Appendix for more detail.

Estimates of the parameters in Equation 1, with the log of total revenue as the dependent variable, are presented in Table 3. All impact estimates are negative and roughly similar in magnitude, ranging from -0.70 (TWFE and DR) to -0.80 (MTWFE). Additionally, all results are significant at the 1% level. Thus, our results show that leaving the California Dungeness crab fishery had a negative impact on fishing revenues during the crab window of the HAB season. Exit impact estimates are large in magnitude, ranging from a 50.3% reduction to a 55.2% reduction in revenues. The magnitude of these losses is consistent with expectations of extreme outcomes from the HAB event, e.g., a complete failure of the California Dungeness crab fishery to open. While such an extreme outcome was outside anything ever before experienced on the West Coast, so was the extended delay. The results raise the question, however, of why vessels did not return to the fishery once it opened. While switching fisheries requires switching gear and cannot happen instantaneously, would vessels have been better off switching even if it meant missing the season opening?

We explore this question with our alternative definition of treatment, which defines a vessel as treated if it failed to participate in a California Dungeness crab opening. The alternative definitions of treatment increase the number of vessels in the treatment group by 12 (55%), 6 (27%), and 3 (14%) when the season opening is defined as the first 2, 4, and 6 weeks respectively. By including vessels that failed to participate in the season opening but did return to participate in the California Dungeness crab fishery later in the season, we can explore whether the magnitude of our impact estimate is reduced. A reduction would suggest that vessels were able to benefit by switching back into the California Dungeness crab fishery after the season started, raising the question of why our treatment group did not switch back. Even with sizable increases in the number of vessels added to the treatment group, Figure 6 shows that loss estimates were not mitigated in any of our alternative definitions of treatment. The robustness of our result to this alternative definition of treatment suggests that participation in the season opening was an important part of mitigating losses from the HAB event.

Finally, we examine whether the reductions in fishing revenues that we estimate correspond to a similar reduction in the number of trips taken. A corresponding reduction in fishing effort could suggest that the fishing revenue losses, experienced by the treatment group, were at least partially made up for by increased opportunities to earn non-fishing income. However, our results do not show strong evidence that exit decision had an impact on trips taken for treated vessels. While the DID estimate from the MTWFE specification is significant at the 10% level, the estimates were insignificant in the TWFE and DR specifications, with the DR specification being our preferred specification (Table 4). Further, the magnitude of the DID estimate was similar to the pre-period DID estimate from the 2014 season as seen in the event study plot (Panel B Panel A of Figure 5).

5 Conclusion

It is becoming increasingly important to understand the relationship between fishing portfolio diversification and the variability in returns from fishing, as fisheries shocks are becoming more common due to climate change, and even potential global health pandemics, and restrictions on fishing access limiting diversification across fisheries or species are growing in many countries worldwide. The previous literature has found that fishing portfolio diversification is correlated with reduced variability in fishing revenue, suggesting that portfolio diversification may be a mechanism that can buffer harvesters from shocks. However, the benefits from diversification will depend on harvesters' investment strategies, for example whether harvesters adopt active or passive investment strategies.

Some unique features of diversification in fisheries may either promote or discourage active investment strategies. On one hand, in contrast to investments in pure financial assets, real estate, art, precious metals, etc., adopting a passive investment strategy may be more challenging in fisheries, because there is no "do nothing" option where decisions from a previous period are automatically applied and returns are generated. In other words, the absence of a "do nothing" option may reduce frictions in reacting to market shocks. On the other hand, because switching between fisheries can involve significant opportunity costs associated with acquiring necessary permits, and preparing fishery-specific gear, vessel, and crew for participation, potentially more significant than transactions costs of active diversification in other markets, there may be pressures towards passive diversification.

The relative performance of these two strategies in fisheries is an open question. In contrast to financial markets, there is no reason to believe the Efficient Market Hypothesis (EMH) governs fisheries returns. Precursors for a fisheries analogue to the EMH may exist. For example, similar to the no-arbitrage conditions under the EMH, fisheries economists have shown that, under open access conditions, opportunities for arbitrage will be eliminated across fisheries and space [Gordon, 1954, Sanchirico and Wilen, 1999]. Additionally, for those fisheries managed with property rights, quota prices are generally believed to be efficient [see e.g. Newell et al., 2005, Jin et al., 2019].[7] However, there are key differences between financial markets and fisheries, including sluggishness in capital adjustments needed to exhaust arbitrage opportunities [Smith, 1968] and infra-marginal rents [Karpoff, 1987, Johnson and Libecap, 1982, Grainger and Costello, 2016].

Therefore it is possible that these differences favor a strategy of holding access to various fisheries as options[8] to be exercised after gathering more information on the state of the world and updating one's forecasts on the returns to various allocations of effort across available fisheries. In other words, an active approach to diversification may yield better performance if harvesters have access to needed information.

However, the information needed to make informed decisions over portfolio shifts is not always available. Our case study illustrates this point. We contribute to understanding outcomes from active versus passive diversification in fisheries in the absence of the information required to make good predictions over returns to participation in one of the West Coast's most important fisheries. Specifically, we use an exogenous and observed shock to the California Dungeness crab fishery, i.e. a HAB event, which we argue generated exogenous variation in portfolio shifts. Our results suggest the strategy of exiting the California Dungeness crab fishery generated revenue losses of 50%-55%, on average.

While our results are contextually dependent and it is possible to imagine an alternative scenario where temporarily exiting the California Dungeness crab fishery would have yielded positive returns, e.g. due to the

[7] Although there is empirical evidence to the contrary in multispecies fisheries, see e.g., Holland [2016].

[8] Not to be confused with options as financial derivatives, which are essentially an insurance policy against unfavorable changes to securities prices.

failure of the Dungeness crab fishery to open, we speculate that the environmental conditions under which the strategy of temporary exit would have generated revenue gains are even more extreme. The magnitude of the Dungeness crab season delay across California was a result of a confluence of several unusual ocean conditions that ultimately resulted in high and persistent levels of domoic acid uptake in Dungeness crab. Thus, it seems likely that an even greater persistence of domoic acid levels over management thresholds represents an even lower probability event than the one we observed.

Our results underscore the potential benefits of developing and/or improving forecasting tools that can enable harvesters to incorporate multiple information streams into short-run and real-time diversification decisions. For example, it is possible that vessel responses to the 2016 HAB event would have been different if harvesters were able to better anticipate the duration of the HAB-related closure. Given the volume of ocean and coastal monitoring data generated in recent decades along with improved prediction methods coming from the field of data science, there is a potential opportunity to improve responses to fishery shocks and, therefore, the benefits from active portfolio management in fisheries.

Future work is needed to gain a more wholistic understanding of the returns to various fisheries diversification strategies. While ideally the relative performance of active versus passive investment strategies could be evaluated in over the long run, and across multiple shocks, there are empirical challenges to such evaluations in a fisheries context. Thus, it is more likely that a wholistic understanding of these impacts will be gained from a collection of empirical case studies, using tools from causal inference, such as ours, coupled with analytical work focused on uncovering the mechanisms determining the returns to various risk mitigating strategies in fisheries.

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Table 1: Variables

Variable	Description	Units	Estimator
Outcome variables:			
revenue	total fishing revenue	million dollars*	all
trip count	number of trips (unique fish tickets)	trips*	all
Impact variables:			
post	2016 season?	0/1	all
trt	exited CA Dungeness in post period?	0/1 [22 vessels]	all
Covariates:			
spec	CA Dungeness crab revenue/ total revenue	fraction†	MTWFE & DR
vessel length	recorded vessel length (may vary by season)	feet †	MTWFE & DR
crab location	revenue weighted mean latitude of Dungeness	decimal degrees†	MTWFE & DR
shannon	Shannon diversification index	index†	MTWFE & DR
Variables for exploration only:			
first season week	season week when first ticket was recorded	weeks after the week of Nov 15^{th}	NA

Note: * indicates the variable is log transformed for analysis; † indicates the variable is lagged for analysis.

Table 2: Summary statistics by treatment status and period

period	pre					post				
group	control		treatment		diff.	control		treatment		diff.
Variable / Stat	N	Mean	N	Mean	p-val	N	Mean	N	Mean	p-val
A.					unmatched sample					
revenue (mn. $)	1099	0.24	85	0.25	0.59	298	0.13	22	0.11	0.51
spec (fraction)	1099	0.87	85	0.68	0***	298	0.92	22	0	0***
vessel length (feet)	1099	40.6	85	43.82	0***	298	40.26	22	43.91	0.11
crab location (dd latitude)	1099	39.2	85	39.07	0.50	298	39.03	5	43.75	0.01**
Shannon (index)	1099	0.28	85	0.54	0***	298	0.17	22	0.29	0.07*
first season week	1099	3.62	85	3.55	0.86	298	19.09	22	12.73	0***
trip count	1099	31.33	85	29.53	0.36	298	17.48	22	14.32	0.13
B.					matched sample					
revenue (mn. $)	87	0.27	85	0.25	0.57	22	0.18	22	0.11	0.17
spec (fraction)	87	0.74	85	0.68	0.08*	22	0.83	22	0	0***
vessel length (feet)	87	44.38	85	43.82	0.73	22	44.18	22	43.91	0.93
crab location (dd latitude)	87	39.05	85	39.07	0.93	22	39.04	5	43.75	0***
Shannon (index)	87	0.49	85	0.54	0.25	22	0.27	22	0.29	0.82
first season week	87	3.13	85	3.55	0.39	22	16.82	22	12.73	0.09*
trip count	87	25.99	85	29.53	0.12	22	17.36	22	14.32	0.29

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

Table 3: Estimated impact of non-participation on total revenue

Dependent Variable:	*log*(*revenue*)		
Variables			
trt x post	-0.700***	-0.804***	-0.696***
	(0.214)	(0.233)	(0.247)
Estimator	TWFE	MTWFE	DR
Fixed-effects			
vessel id	Yes	Yes	No
season	Yes	Yes	No
Fit statistics			
Observations	1,504	216	1,230
R^2	0.839	0.837	-
Within R^2	0.034	0.132	-

Clustered (vessel id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: Estimated impact of non-participation on total trips

Dependent Variable:		*log*(*trips*)	
Variables			
trt x post	-0.137	-0.292*	-0.130
	(0.152)	(0.172)	(0.135)
Estimator	TWFE	MTWFE	DR
Fixed-effects			
vessel id	Yes	Yes	No
season	Yes	Yes	No
Fit statistics			
Observations	1,504	216	1,230
R^2	0.749	0.694	-
Within R^2	0.002	0.035	-

Clustered (vessel id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

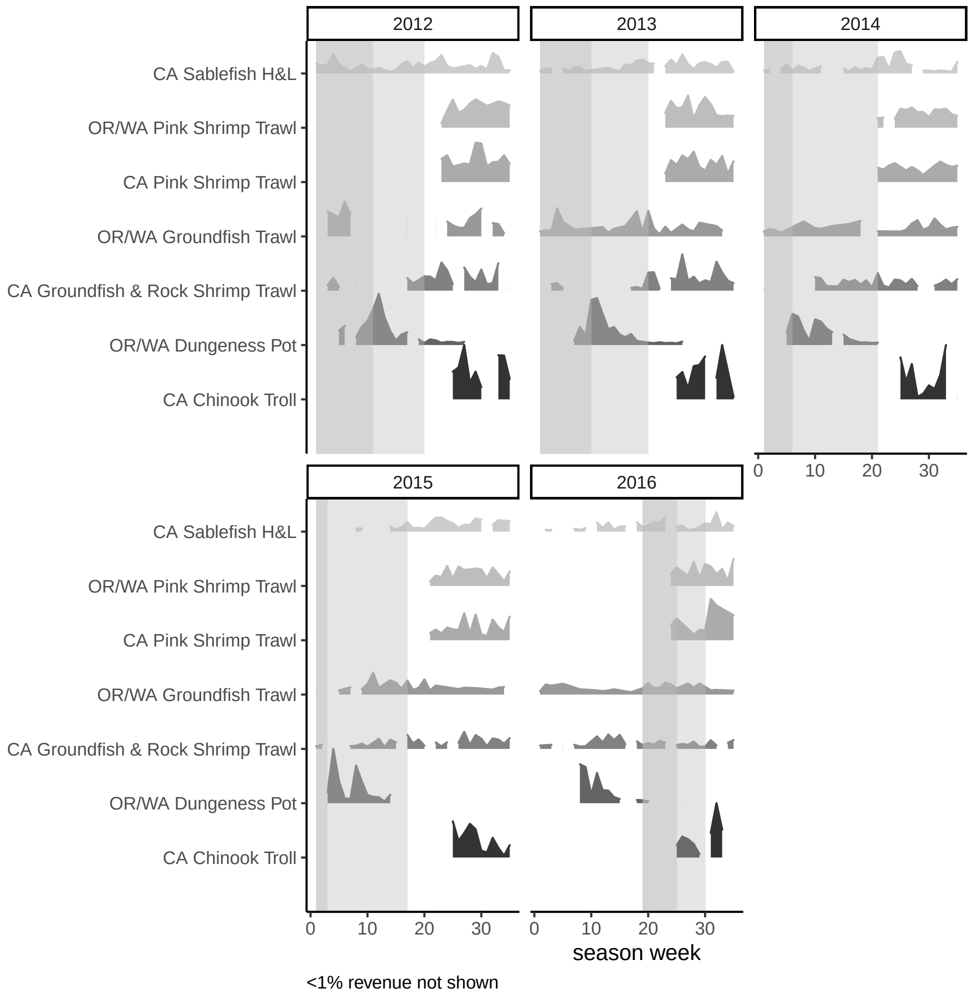

Figure 1: The distribution of fishing revenues earned by vessels in our sample, by season and across the crab window, for the metier fisheries that account for at least 1% of fishing revenue earned by vessels in our sample during the crab season. The dark shaded region of each seasonal plot represents the timespan during which at least 50% of California Dungeness crab revenue was generated. The light shaded region of each seasonal plot represents the timespan during which at least 90% of California Dungeness crab revenue was generated.

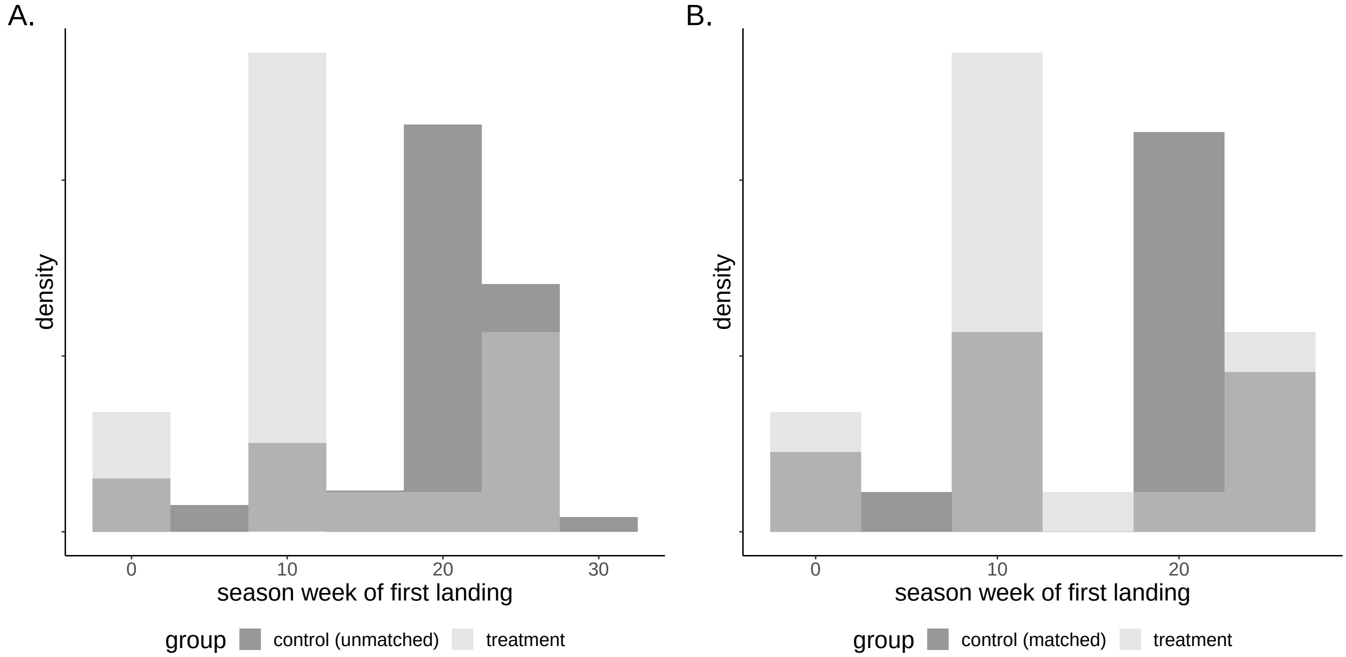

Figure 2: Distributions of week of first landing in the 2016 season for treated and control groups. Panels A and B display data from the unmatched and matched samples respectively.

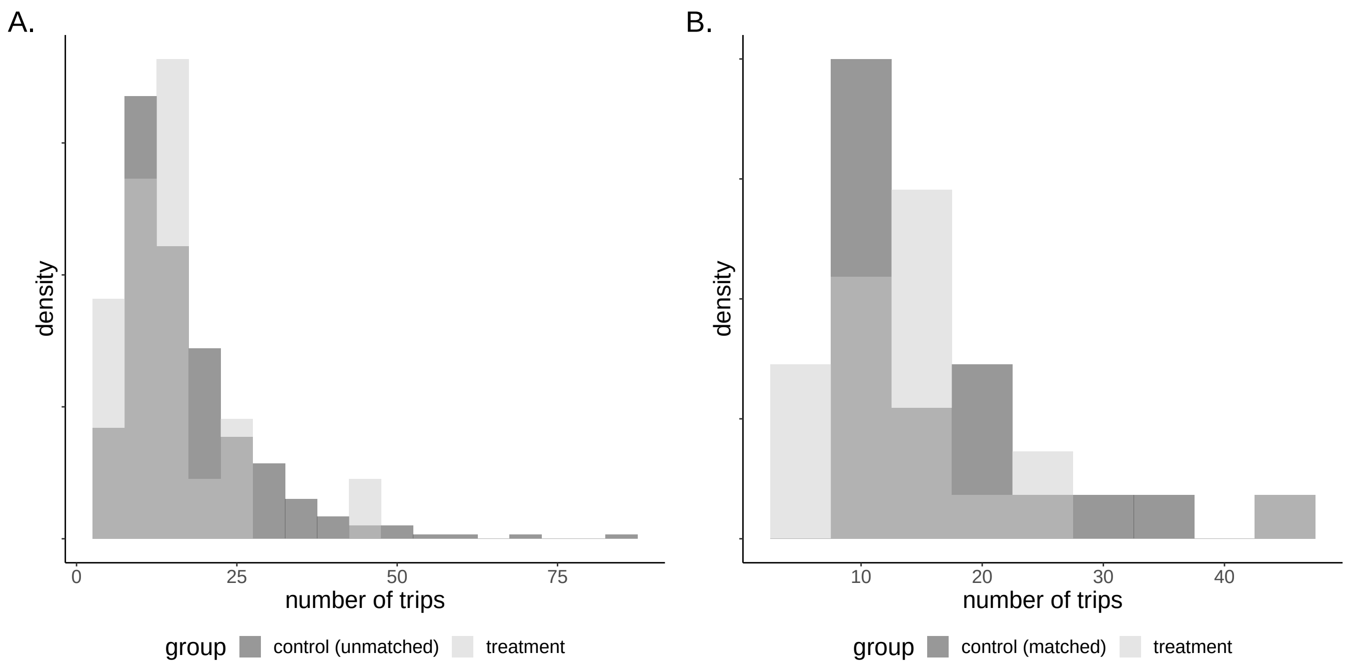

Figure 3: Distributions of the total number of trips (recorded landings) in the 2016 season for treated and control groups. Panels A and B display data from the unmatched and matched samples respectively.

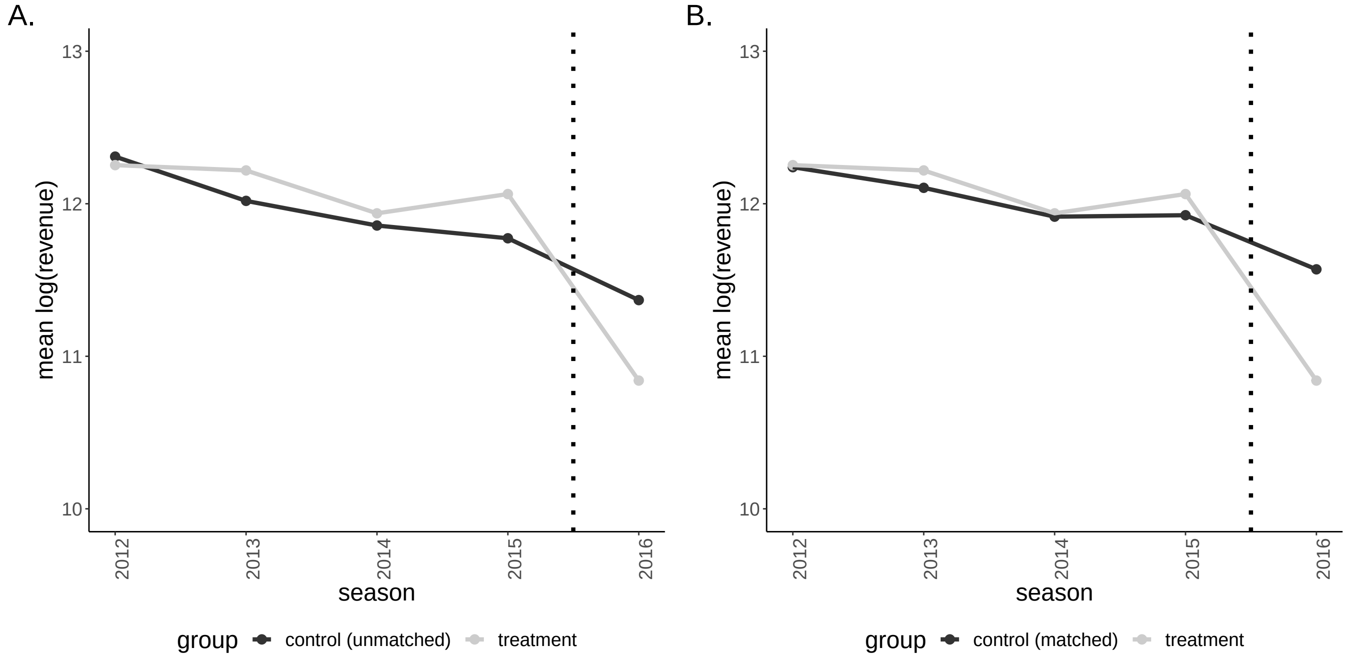

Figure 4: Mean log revenue by treatment status over time for the unmatched (Panel A) and matched sample (Panel B).

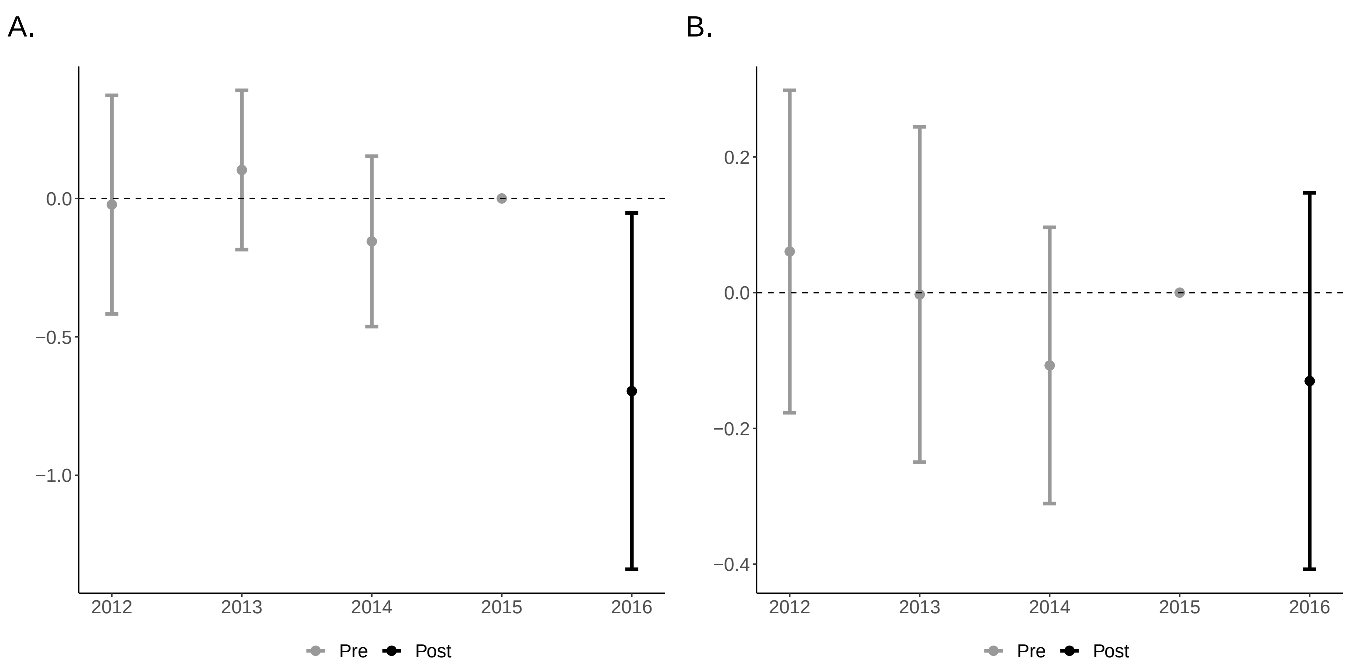

Figure 5: Event study results from the doubly robust estimator when using the log of revenue as the dependent variable (Panel A) and the log of trip count as the dependent variable (Panel B)

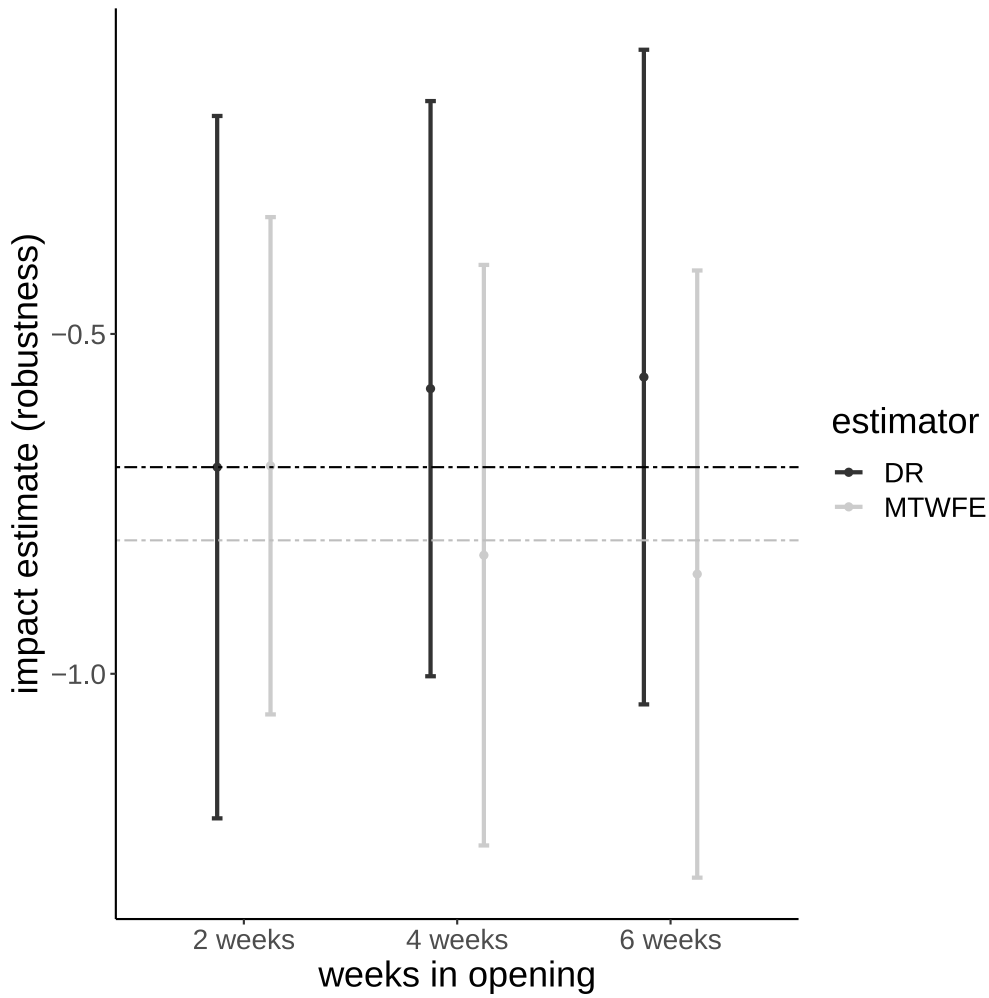

Figure 6: Estimated impacts with an alternative definition of treatment: non-participation in the California Dungeness crab season opening in 2016 when a vessel had participated in the opening in 2015. The dashed lines show the point estimate from our main results from the DR (black) and MTWFE (grey) estimators.

Appendix to Fishing Portfolio Response to a Climate Shock

5.1 Defining Métier Fisheries

We define a vessel's fishing portfolio based on the fisheries that were targeted by the vessel throughout the year. While it is possible to assume each species or each species-gear combination identify a fishery, there are 348 unique species-gear combinations in California alone during the 2011-2016 season crab windows, and many of these species-gear combinations regularly co-occur within a fishing trip suggesting they are caught together as part of the same fish assemblage.

To identify distinct fisheries, we use a procedure based on the métier analyses conducted in Fuller et al. [2017] and Fisher et al. [2021], which similarly focused on the U.S. West Coast and California fisheries, respectively. We treat California and Oregon/Washington as two distinct regions, and run the analysis separately for the two regions. Rare species-gear combinations comprising less than 0.05% of a region's revenue, or that occur in less than 0.05% of regional trips, are redefined as a miscellaneous species within the gear type.

To identify target fisheries, we create a network of trip similarities consisting of all trips in our period of study (during the crab windows of 2011-2016), and identify the clusters of trips that share similar catch compositions, defined as targeting the same fish assemblage with the same gear. We start by identifying the revenue composition 'distance' between each pair of trips. Distance (D_{ij}) is measured as the Hellinger distance between trip i and j,

$$D_{ij} = \sqrt{\sum_k (\sqrt{p_{ik}} - \sqrt{p_{jk}})^2}, \tag{2}$$

where p_{ik} equals the proportion of revenue generated in trip i from species-gear combination k.

The distance matrix is converted into a similarity matrix S, scaled [0,1],

$$S_{ij} = 1 - D_{ij}/max(D), \tag{3}$$

which is a relational matrix that allows trip similarities to be represented as a large, undirected network. Network nodes represent trips and the weighted edges represent similarities in the revenue-weighted fish assemblages.

We use the infoMap algorithm Rosvall and Bergstrom [2008] to identify clusters of trips with similar landing compositions, and we define each cluster as a unique fishery. InfoMap is a cluster-detection algorithm that is used to identify network sub-graphs where the nodes in the sub-graph are relatively densely connected to one another compared to their connection to the larger network outside the sub-graph. The algorithm assigns each node to one cluster and only one cluster.

Due to the large sizes of the matrixes, there is computational difficulty in including all trips within the algorithm. Therefore, we apply the algorithm to a subset of our data consisting of all trips in the 2014 crab window. We chose 2014 because it is in the middle of the panel occurs and before the harmful algal bloom event. We then use nearest-neighbor matching to assign the remaining trips to a cluster based on whichever trip in 2014 it most closely resembles in terms of Euclidean distance.

Fishery names are assigned based on the combination of species that comprise at least 70% of the total revenue for the cluster. For the largest fisheries, this is usually a single species. An exception to this convention is the groundfish cluster, which includes trawl-caught sablefish and various species of sole.

5.2 Sensitivity to Violations of Parallel Trends

We conduct a sensitivity analysis proposed by Rambachan and Roth (2023), i.e., the "sensitivity analysis using relative magnitudes restrictions". Essentially, the sensitivity analysis determines how large a violation in the parallel trends assumption would be needed for the estimate of the δ, or difference-in-differences, parameter to go from being statistically significant to insignificant. Violations are expressed relative to pre-period violations in parallel trends, as calculated by an event study, and relative magnitude violations are denoted by $\bar{M}$.

Figure A1 shows the results of our sensitivity analysis for the unmatched (left) and matched (right) samples. We find similar results for both samples in that our result is robust to allowing for violations of parallel trends up to 1.75 times as big as the maximum violation in the pre-treatment period.

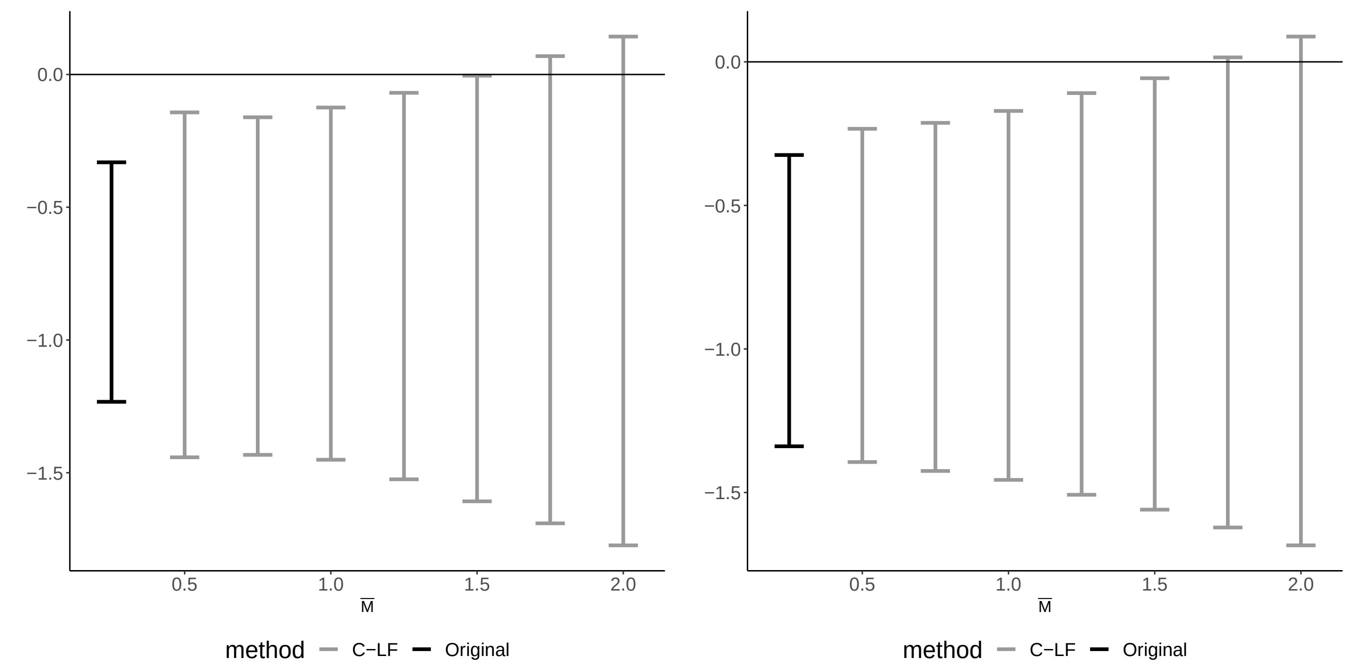

Figure A1: Confidence intervals around the DID estimates that adjust for violations of parallel trends expressed as a fraction of the maximum violation of parallel trends in the pre-treatment period.