ESSAYS EXAMINING HAWAI‘I’S LONGLINE FISHERY

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Much of what is presented in these chapters draws heavily from projects completed in collaboration with my committee members. However, any remaining errors are my own.

Abstract

Fisheries are a textbook example of market failure in which rational behavior does not necessarily lead to socially optimal outcomes. Instead, individual incentives often lead to over-exploitation of marine species. Regulations attempt to mitigate against the tragedy of the commons but do not always succeed. The essays in this dissertation examine a variety of regulatory tools that are used in the Hawaii longline fishery.

Estimating the spillover benefits of Marine Protected Areas (MPAs) is complicated by endogeneity and selection biases. Most causal evidence of spillover benefits has come from relatively small MPAs. The potential for large MPAs to provide a refuge (and subsequent spillover) for highly migratory species has traditionally been doubted because most MPAs are small relative to the range of highly pelagic species. In the first chapter, we test for evidence of biological spillovers accruing from the world's largest, fully no-take MPA, Papahānamokuākea Marine National Monument (PMNM). We account for differences in migratory patterns across species and heterogeneity across fishing boats by employing species-specific difference-in-differences models with boat fixed effects. Using independent observer data, we compare catch-per-unit-effort near and from the MPA for the exact same vessel before and after expansion of the MPA. Though the large-scale expansion of PMNM occurred fairly recently, our findings suggest evidence of positive spillover benefits for yellowfin and bigeye tuna, the main target species in this region. We observe the same results using logbook data self-reported by boat captains.

The stringency of environmental regulation of tuna production in the Pacific Ocean varies temporally, spatially, and cross-sectionally for US-registered firms. In the second chapter, we use this variation, which is exogenous to changes in trade policy, to test a central tenet of the Pollution Haven Hypothesis: more stringent environmental regulation causes firms

to relocate to less regulated regions and may not reduce aggregate environmental harm. Double- and triple-difference tests on changes in daily production decisions provide causal evidence in support of the hypothesis. Firms relocate over 600 miles within a few weeks of new regulatory measures. We do not observe reductions in aggregate environmental damage and, in some years, more stringent regulations cause more environmental harm than would be observed in the absence of these regulations.

In the final chapter, we identify exogenous shifts in market supply of fish by utilizing extreme weather events out at sea to obtain an unbiased estimate of the inverse price elasticity of demand for Pacific bigeye tuna. Utilizing a standard ordinary least squares model, we tend to overestimate the elasticity of demand. Once correcting for endogeneity, we find demand for bigeye tuna to be more inelastic.

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Chapter 1

Initial Evidence of Spillover Benefits from the World's Largest Marine Reserve

1.1 Introduction

The controversy over the benefits of no-take Marine Protected Areas (MPAs) for highly pelagic species has been ongoing since the late 1990s. Conservationists praise MPAs for reversing species decline and ensuring the health of marine ecosystems by protecting biodiversity (Gell and Roberts, 2003; Edgar et al., 2014), which should indirectly benefit pelagic species. On the other hand, critics have argued that most targeted pelagic species are too migratory to enjoy real protections from MPAs and any gains that could be attained are negated by large economic losses (Babcock et al., 2010; Curnick et al., 2020).

The world's largest, fully no-take MPA, Papahānamokuākea Marine National Monument (PMNM) is a prime example of this controversy.[1] Previous studies have attempted to estimate the economic cost associated with the foregone fishing activity that would have otherwise occurred within PMNM yet the magnitude of loss is still inconclusive (Lynham et al., 2020; Chan, 2020; Sweeney, 2021; Lynham et al., 2021). Moreover, a conclusive

[1]There are currently two MPAs larger than PMNM (Marae Moana in the Cook Islands and the Ross Sea Region Marine Protected Area) but both allow some fishing to take place within the MPA. We use the term "marine reserve" in this paper to refer to a fully protected MPA such as PMNM where no fishing or mining is allowed but some authors use the term differently.

assessment of the total economics impacts of PMNM must also estimate the potential benefit of establishing the MPA.

An MPA can provide economic benefits while still satisfying conservation goals if the economic gains to adjacent fishing grounds exceed the economic losses caused by the MPA (Smith et al., 2006). But if losses due to the lost area are coupled with little to no spillover benefits, the profitability of the associated fishery would be harmed. There is some evidence to support the argument that the opportunity cost of an MPA can be offset by an increase in fishing productivity in adjacent areas. Historically, within reserve boundaries, an increase in biomass has predominantly been observed among more sedentary species, with more limited evidence for mobile species (Gell and Roberts, 2003). The continuity of habitat across MPA borders and species mobility patterns appear to strongly determine the presence of MPA spillovers (Moffitt et al., 2009; Grüss et al., 2011; Harmelin-Vivien et al., 2008). Another key factor is whether MPAs protect known spawning grounds or nurseries, and thus serve as a source for larvae and juvenile fish (Sanchirico and Wilen, 2001). For example, evidence of tuna spawning grounds have been observed in the Phoenix Island Protected Area located in the southern Pacific Ocean (Hernández et al., 2019). More relevant to PMNM, the near-shore waters off the coast of the Hawaiian Islands have been shown to act as nurseries for yellowfin tuna (Lam et al., 2020). Furthermore, analysis of oxygen and carbon isotopes in otolith cores have provided strong evidence that 91% of young yellowfin tuna caught near the Hawaiian islands have originated from nearshore Hawaiian waters and choose to remain in the surrounding areas (Wells et al., 2012).

The crux of the debate over MPA benefits for highly pelagic species comes down to two questions: how big can MPAs get and how far do pelagic species actually migrate? The first question is in some ways tautological: assuming sufficient changes in the Convention on the Law of the Sea, an MPA can be made big enough to benefit any highly pelagic species. As an extreme example, if the entire high seas area of the world's oceans was turned into a no-take MPA, there is little doubt that populations of pelagic species such as bigeye and yellowfin tuna would benefit and recover over time (White and Costello, 2014). The more challenging question is just how far does the average bigeye and yellowfin tuna travel in its lifetime and what does that imply about the MPA size required to provide sufficient protection from

fishing in order to allow for additional growth and reproduction. In particular, if previous estimates of the range of some species are being downsized, then that implies the case for MPA spillovers is getting stronger (holding all other factors, including MPA size, fixed). A large body of work by David Itano and colleagues suggests that the range of yellowfin tuna in the Pacific is smaller than previously assumed and, in some cases, still assumed by fisheries management bodies: "yellowfin recaptures indicate movement or vulnerability towards and near the main Hawaiian Islands, whereas bigeye recaptures have remained more offshore in nature from within and outside the EEZ" (Itano and Holland, 2000) and "T. albacares collected in Hawaii were exclusively from local sources; however, a large fraction of T. obesus in Hawaii were classified to the central equatorial region" (Rooker et al., 2016).

The aim of this study is to estimate the extent to which biological spillovers, if any, have occurred since the large-scale expansion of PMNM in 2016. To account for the species-specific biological benefits offered by an MPA, we run a species-by-species difference-in-differences vessel fixed effects model on fishing activity near and far from the largest fully no-take MPA on earth. By creating a species-specific panel that varies spatially, we compare fishing catch close to the reserve to catch farther away from the reserve by the same vessel. Controlling for fishing efficiencies that are heterogenous across vessels and accounting for the migratory patterns of each species, we obtain statistically significant estimates of positive spillover benefits for a number of species, especially the heavily fished but less migratory yellowfin tuna. Results are largely the same whether we use independent observer data or logbook data recorded by captains.

1.2 Background

The presence of an MPA spillover has been documented through biomass trends that occur spatially, fishing effort that is collected through surveys, and data analysis of catch or catch per unit effort (CPUE). Using underwater imagery, a negative relationship between distance from border and biomass has been estimated indicating evidence of biological spillover in six different Mediterranean MPAs (Harmelin-Vivien et al., 2008). An increase in catch and a concentration of fishing effort has been observed in adjacent fishing grounds even when

habitat effects have been controlled for (Goñi et al., 2008; Stobart et al., 2009; Kerwath et al., 2013). It should be noted that many of these studies rely on correlative not causal evidence.

Marine reserves are more likely to provide positive net benefits for fisheries suffering from over-exploitation. When a fishery is over-harvested, marine reserves can achieve higher spillover benefits relative to a well-managed fishery (Buxton et al., 2014; Lester et al., 2009). Bigeye tuna and yellowfin tuna are the two main target species among deep-set longline vessels based out of Hawaii. With a growing market demand and a high commercial value, these species are vulnerable to population decline.

1.2.1 Papahānamokuākea Marine National Monument

The first marine reserve was established off the east coast of Florida by President Theodore Roosevelt in 1903, though this form of management did not gain traction until the latter part of the 20th century. By 1995 there were about 1,306 MPAs established globally and as of 2011, MPAs accounted for 1.3% of the world's ocean area, and 3.2% of ocean area under national jurisdiction (McCay and Jones, 2011).

Located west of the Hawaiian Islands, Papahānamokuākea is one of the world's largest MPAs, spanning 582,578 mi^2, and currently the largest fully-protected no-take MPA or "marine reserve". The history of the site dates back to the initial conservation efforts that took place in the North West Hawaiian Islands (NWHI) in 1909 when a small area was designated as a refuge for seabird nesting colonies. It wasn't until nearly 100 years later, in 2006, that this area would be expanded making it the single largest reserve under the U.S. flag and renamed Papahānamokuākea Marine National Monument by President G.W. Bush (Kikiloi et al., 2017). In 2016, the boundaries were further expanded by President Barack Obama making it the largest, contiguous reserve within a single national jurisdiction. Deep-sea corals, sponges, and other similar species are indicators of healthy biodiversity in the deep seas and blooms of these types of specimens have been discovered in the expanded PMNM region (Kelley et al., 2019).

1.3 Analysis

1.3.1 Data

The longline fishery is one of the most profitable fishing fleets in Hawaii. In 1980, there was a rapid expansion of the longline fleet which lead to concerns of over-exploitation of marine resources. An initiative took place in 1993 to better document fishing activity by placing observers on longline vessels. By 2004, there was 100% observer coverage on the shallow-set portion of the longline fleet and 20% coverage on the deep-set portion (Brooke, 2012). Shallow and deep refers to the depth at which the long lines of baited hooks "soak" in the water. The National Marine Fishery Service (NMFS) manages the data collected by the observer program which is the data set used in this analysis. Observer data includes shallow-set and deep-set fishing trips that were conducted by Hawaii and American Samoa vessels. The vast majority of fishing (and observer data) is done by the Hawaii deep-set fishery, so we chose to focus our attention on Hawaii deep-set catch only.

The Papahānamokuākea expansion took place in 2016 so we restrict our data set to observations between 2010 and 2019 (the most recent data available). The observer data is recorded at the individual fish level, so we start by aggregating catch such that we obtain a total number of species z caught by fishing set s. To control for captain efficiency, we leverage the *permit number* of each observation as a captain identifier. Set attributes include the time and location of the following: when the hooks were set in the water (*begin set*), when the hooks were pulled from the water (*begin haul*), and when the set was completed (*end set*). We use the location of *begin set* to identify sets made near and far from PMNM. Additional information on gear type is also recorded and used as controls in our final model (e.g., number of hooks used, number of hooks per float, number of light sticks used, light stick color, etc). Bigeye and yellowfin tuna are the main targets for the deep-set fishery, so we measure the individual spillover for these two species. In addition, we also estimate a spillover effect for all species caught, regardless of commercial value.

1.3.2 Methods

Estimating a causal spillover from an MPA can be difficult due to two main endogeneity concerns. The first concern is the natural time trend of the fishery. Fishery characteristics such as fleet size, advancements in fishing technology, and species populations are changing over time. Simply comparing fishing conditions before and after MPA establishment fails to control for these time trends, potentially leading to biased estimates. The second concern is heterogeneity in captain efficiency. It is plausible that more efficient captains might fish closer to an MPA after it is created so a purely spatial comparison of catch without controlling for heterogeneities across captains would lead to biased results. For example, a researcher might think they are estimating a spatial change in fish abundance but, in reality, they are estimating a spatial change in fishing effort.

The economics literature typically tackles these concerns utilizing a difference-in-differences (diff-in-diff) model with fixed effects. The proposed modeling framework controls for endogeneity that would otherwise arise due to selection bias or time trend bias by comparing fishing productivity between a predefined "treatment" and "control" group, before and after the MPA was established. Our analysis closely follows Smith et al. (2006) which measures the biological spillover from two MPAs in the Gulf of Mexico. The authors build their difference-in-differences model by controlling for gear type, differences in captain skill, spatial distribution of fish stocks, seasonal fluctuations, and the effects of co-existing policies.

Similar to Smith et al. (2006), we specify our treatment and control group based off of distance from the PMNM border. We start by defining a "near" region that extends between (0, x] miles from the MPA border and a "far" region that extends (x, 2x] miles from the MPA border. The treated group will be any vessel that fishes in the near region and the control group would be defined as any vessel who fishes in the far region. We arbitrarily choose x to be 100-, 200-, and 300-miles as our main region-radius specifications, but as a robustness check, we also run our models using a *continuous distance* variable defined as miles away from PMNM. The diff-in-diff estimator will measure the benefit, if any, of fishing close to the monument after the monument borders were expanded. Our main outcome variable is relative CPUE, which we define as catch per 1,000 hooks divided by the pre-expansion CPUE mean of the sample, for each specie groups being examined (Equation

1.1). In other words, for each set i that was made on day t, we calculate relative CPUE for species v by dividing catch per 1,000 hooks by the average CPUE recorded between [0, 2x] miles away from PMNM, pre-expansion. This outcome variable allows us to easily compare changes in CPUE across species and species groups: coefficients in our regressions can be interpreted as the percentage increase or decrease relative to mean pre-expansion CPUE. Table (1.1) summarizes the pre-expansion average CPUE values by species and by region-radius specification.

$$relativeCPUE_{i,t} = \frac{CPUE_{i,t}}{mean(CPUE_{t \leq ExpansionDate})} \tag{1.1}$$

Table 1.1: Pre-Expansion Statistics: Pre-expansion average CPUE across the entire fishing area (both 'near' and 'far' region) for each region-radii specification.

SPECIES	Radius 100	Radius 200	Radius 300
All	23.67	23.58	23.83
BIGEYE_TUNA	4.30	4.44	4.49
OTHER	18.34	18.22	18.57
YELLOWFIN_TUNA	1.03	0.92	0.78

We start by visually comparing fishing conditions near and far from PMNM, for each of the 100-, 200-, and 300- region-radius specifications (Figure 1.1). For each year, y, we visualize average annual differences in CPUE ($dCPUE_y$) between the near and far regions (see Equation 1.2). We then standardize by subtracting the pre-expansion mean difference and dividing by the pre-expansion standard deviation (Equation 1.3). Each data point on the graph can be interpreted as the number of standard deviations away from the pre-expansion mean difference in CPUE. We plot the time trends of these differences for bigeye, yellowfin, and all species caught. The black vertical line is set at year 2016 to indicate the expansion year.

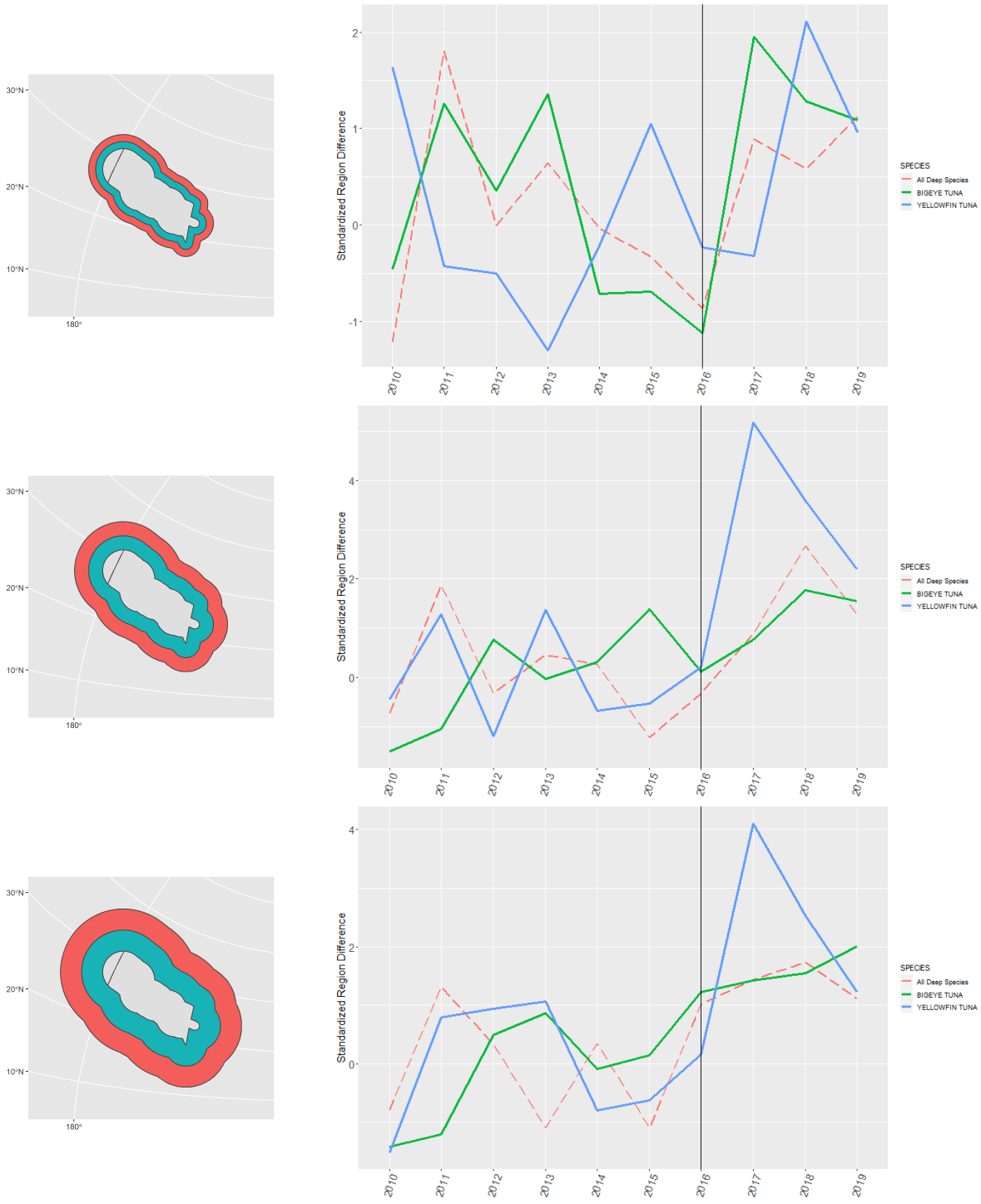

Figure 1.1: Time Trends Between Regions: Plots visually compare CPUE between 'near' and 'far'. Each trend line represents the difference such that positive values indicate higher CPUE in the 'near' region for each of the 100-, 200-, and 300- region-radius specifications. Negative values indicate higher CPUE in the 'far' region.

$$dCPUE_y = CPUE_{near} - CPUE_{far} \tag{1.2}$$

$$standardized\ dCPUE_y = (dCPUE_y - mean(dCPUE_{y\leq 2016}))/sd(dCPUE_{y\leq 2016}) \tag{1.3}$$

After the monument was expanded, at a 100-mile region-radius, catch for bigeye and yellowfin tuna was slightly higher in the near region relative to the far region (reflected by the positive time trend) and all-species caught remained relatively constant between the two fishing regions. As we expand our region-radius to reflect $x = 200$ miles, vessels fishing close to the monument, after the expansion, observed much higher yellowfin catch. Catch for bigeye and for all-species was slightly higher after PMNM was expanded. Expanding our region-radius a third time, $x = 300$ miles, the relationship between catch and distance strengthens. In our 300-mile specification we see a positive effect for vessels fishing near to PMNM across both tuna species and for all species caught.

1.3.3 Model

We introduce four different model specifications, each one imposing additional controls with every model iteration (refer to Equations 1.4, 1.5, 1.6, and 1.7). The base model, represented by Equation (1.4), is a diff-in-diff model without fixed effects. Our variable of interest is relative CPUE, $CPUE_{s,i,t}$, for set s, made by vessel i, on day t. The time treatment, $ExpansionDummy_t$, will take a value of 1 if day t took place after the expansion and 0 otherwise. Our treatment, or distance indicator, $DistDummy_{s,t}$, takes a value of 1 if set s was made in the "near" fishing region and a 0 if the set was made in the "far" fishing region. The last term in Equation (1.4) will be the difference-in-differences coefficient making β_3 our variable of interest. β_3 measures the benefit of fishing close to the monument, after the monument borders were expanded, thus a positive β_3 indicates evidence of a biological spillover and a negative coefficient indicates a negative spillover effect. Because we define our outcome variable as 'relative CPUE', all coefficients can be interpreted as percentage changes from the average pre-expansion CPUE. We use robust standard errors, $\epsilon_{s,i,t}$, across

all model specifications.

The No-FE model, represented by Equation (1.4), measures the spillover effect only and does not control for captain efficiency or seasonality. This model acts as our baseline comparison. As a means to control for intra- and inter- annual variation and heterogeneity across captains, we use month-year and captain fixed effects (refer to Equation 1.5). The Captain/MonthYr model controls for natural time trends and captain efficiency by incorporating vessel level fixed effects, $\mathbf{V}_i$ and month-year fixed effects, $\mathbf{MY}_t$.

Underwater topography is extremely influential on fishing productivity. Initially, we hoped we could define our region-radii based off of seamount distribution. Unfortunately, seamounts do not follow a distinct pattern so defining our radii based off of seamount distribution would be impossible. Instead, we incorporated the presence of a seamount by intersecting set location with seamount base and flagging all fishing sets that took place above the base of a seamount, refer to Equation (1.6). We further build our identification strategy by adding in two variables to control for seamounts. We control for seamounts by including $SeamountDEPTH_{s,i,t}$, a continuous variable that takes a positive value for the depth of seamount peak. For sets that were not made over a seamount, average ocean depth is recorded. Seamount depth ranges between 46 meters to 4,740 meters below the ocean surface. The average ocean depth is 4280 meters.

Finally, our fourth model specification, the "Kitchen Sink" approach represented by Equation (1.7), incorporates as many controls as possible making this specification our most restrictive model. In addition to the vessel, time, and seamount controls, the Kitchen Sink approach incorporates a vector of gear covariates which controls for variables like bait type, hooks per float, and float line diameter.

$$\begin{aligned} CPUE_{s,i,t} = \beta_1 ExpansionDummy_t + \beta_2 DistDummy_{s,t} \\ + \beta_3 (ExpansionDummy * DistDummy) + \epsilon_{s,i,t} \end{aligned} \tag{1.4}$$

$$CPUE_{s,i,t} = \beta_1 ExpansionDummy_t + \beta_2 DistDummy_{s,t} + \beta_3(ExpansionDummy * DistDummy) + \mathbf{V}_i + \mathbf{MY}_t + \epsilon_{s,i,t} \quad (1.5)$$

$$CPUE_{s,i,t} = \beta_1 ExpansionDummy_t + \beta_2 DistDummy_{s,t} + \beta_3(ExpansionDummy * DistDummy) + \mathbf{V}_i + \mathbf{MY}_t + SeamountDEPTH_{s,i,t} + \epsilon_{s,i,t} \quad (1.6)$$

$$CPUE_{s,i,t} = \beta_1 ExpansionDummy_t + \beta_2 DistDummy_{s,t} + \beta_3(ExpansionDummy * DistDummy) + \mathbf{V}_i + \mathbf{MY}_t + SeamountDummy_{s,i,t} + SeamountDEPTH_{s,i,t} + \mathbf{GEAR}_{s,i,t} + \epsilon_{s,i,t} \quad (1.7)$$

To measure spillovers for each target species and spillovers for overall catch, we run an all-species analysis and a species-specific analysis. For each of the radii specifications, we first run all four models on the full data set which includes all species caught and does not control for differences among species traits or differences among target species and bycatch. To account for variability in species characteristics, we disaggregate the catch data and focus on the two main target species: bigeye and yellowfin tuna. We then run each model using the three different region-radii specifications on the two species specific data sets.

1.4 Results

1.4.1 Distance Indicator: Region-Radius

We specify our model based on species group (bigeye, yellowfin, other, and all), controls (No FE, Captain/Time FE, Seamount FE, and Kitchen Sink FE), and distance specification (100-, 200-, and 300-mile specification). In total, we have 48 different models. To summarize our final results, we present our regression outputs in graphical form in Figures (1.2), (1.3), and (1.4). The diff-in-diff coefficient is plotted, color coded based off of statistical significance, and bounded with 95% confidence intervals. Each specification with different controls is presented in each of the four panels. For comparison, we include an "other" species group, which is defined as relative CPUE of all other species caught excluding bigeye and yellowfin. In addition, we provide more complete regression output for the 100-mile, "Kitchen Sink" specification for each of the species groups (Table 1.2). Although the visual time trends for this specification in Figure 1.1 appeared to be the least convincing evidence for a spillover benefit, once we control for many of the other factors that influence CPUE, these are some of our most convincing regression results. The spillover benefit is statistically significant for yellowfin at the 5% level, for bigeye at the 10% level, and for all species caught at the 11% level. The coefficient on yellowfin implies that CPUE is 54.8% higher near the MPA after the establishment of the MPA, relative to average CPUE before establishment. Additional regression tables can be found in the Appendix.

Figure 1.2 summarize regression results for the 100-mile region-radius specification. The near fishing region expands between [0, 100] miles away from the MPA border and the far region expands between (100, 200] miles away from the MPA border. Yellowfin catch was statistically higher when fishing close to the monument as shown by the positive diff-in-diff estimator. The coefficient for bigeye tuna is less conspicuous but suggests a slight positive spillover presence but is not statistically significant across fixed effect specifications. Overall, there is weak evidence that vessels catch more fish overall when fishing within 100-miles from PMNM under certain specifications.

We expand our region-radius specification to 200-miles and display the results in Figure 1.3. Sets made between [0, 200] miles observe higher relative CPUE then sets made between

(200, 400] for yellowfin and bigeye. Again, more tuna fish are now being caught near PMNM as opposed to more distant fishing grounds. There is some weak evidence that this also applies to all fish species caught.

We expand our region-radius even further to a 300-mile specification, as shown in Figure 1.4. We continue to see a statistically significant positive spillover for yellowfin tuna and a slightly weak positive spillover for bigeye tuna, though the significance of our bigeye estimates are not robust across fixed effect specifications. There is also weak evidence of a positive spillover for all species caught.

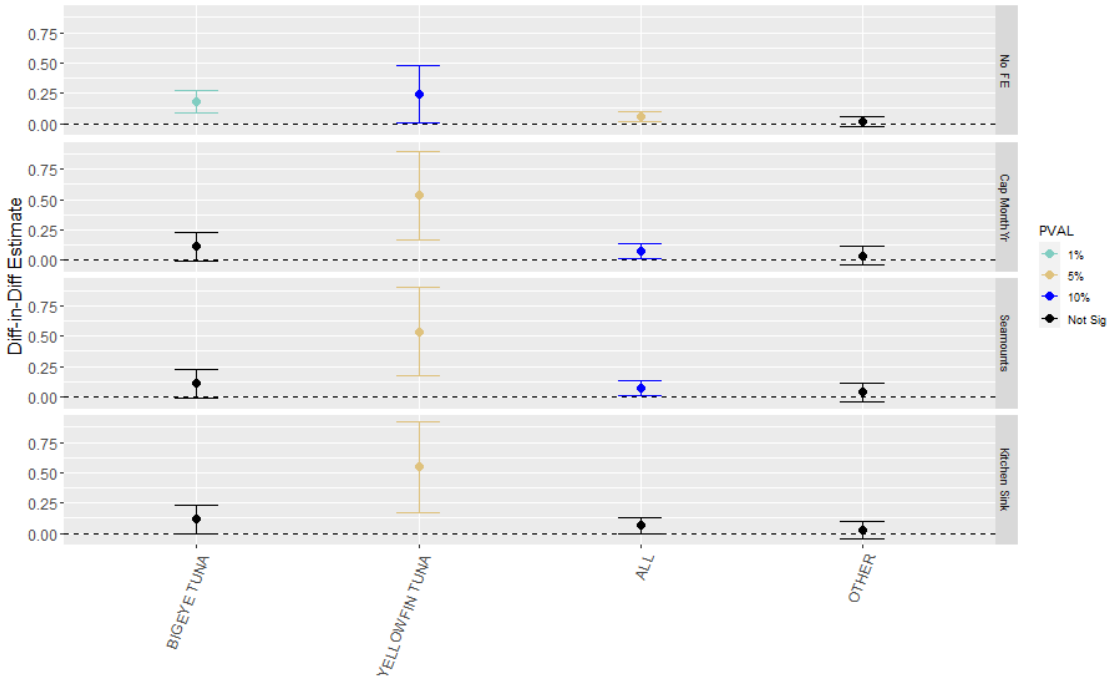

Figure 1.2: 100 Mile Region-Radius: Before the expansion of PMNM, there were 141 active permits fishing in the near and far regions collectively. 118 of them fished in both donuts. After the expansion, there were 114 active permits fishing in the near and far regions collectively. 72 of them fished in both donuts.

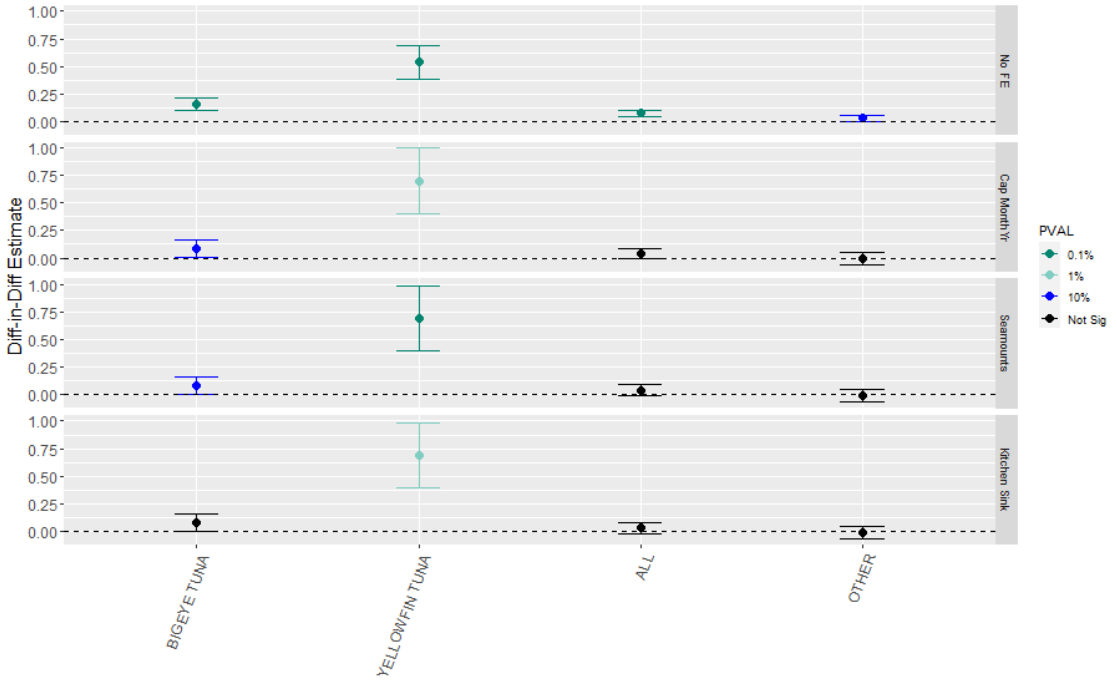

Figure 1.3: 200 Mile Region-Radius: Before the expansion of PMNM, there were 149 active permits fishing in the near and far regions collectively. 138 of them fished in both donuts. After the expansion, there were 135 active permits fishing in the near and far regions collectively. 111 of them fished in both donuts

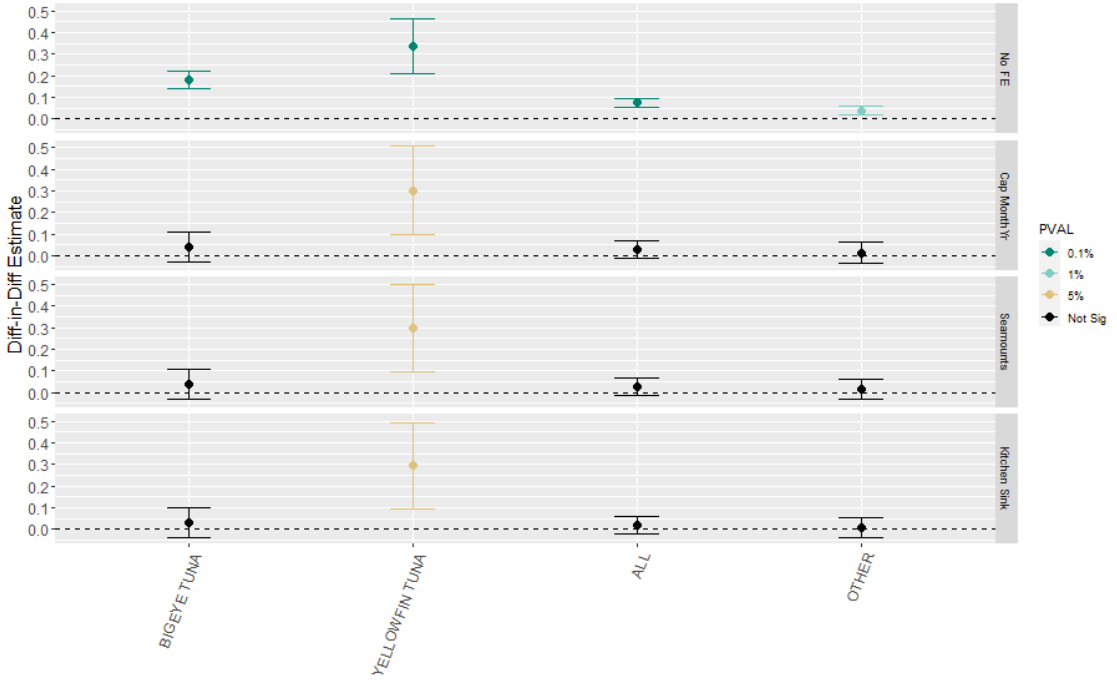

Figure 1.4: 300 Mile Region-Radius: Before the expansion of PMNM, there were 150 active permits fishing in the near and far regions collectively. 143 of them fished in both donuts. After the expansion, there were 140 active permits fishing in the near and far regions collectively. 126 of them fished in both donuts.

Table 1.2: Kitchen Sink (100 Mile Region-Radius): Heterogeneity across captain efficiency, natural time trends, seamount sets, and various gear are controlled for. Each successive column displays results for each species group Bigeye, Yellowfin, All, and Other, using a difference-in-difference regression. DID coefficients measure the effect of fishing close to PMNM after PMNM was expanded in the 2016. The sample runs from January 6, 2010 to January 11, 2020. *p<0.1; **p<0.05; ***p<0.01 Heteroskedasticity-robust standard errors presented in parentheses.

	Bigeye	Yellowfin	All	Other
	(1)	(2)	(3)	(4)
Diff in Diff	0.116*	0.548**	0.064	0.024
	(0.070)	(0.229)	(0.040)	(0.045)
Expansion Dummy	−0.274*	−2.694***	−0.592***	−0.546***
	(0.157)	(0.830)	(0.096)	(0.144)
Distance Dummy	−0.037	−0.033	−0.008	0.001
	(0.037)	(0.108)	(0.025)	(0.030)
Observations	5,571	5,571	5,571	5,569
R^2	0.142	0.177	0.157	0.158

1.4.2 Distance Indicator: Continuous Distance

To gauge how robust our results are to the arbitrarily chosen region-radii specifications, we chose to redefine our distance dummy as a continuous variable. In our previous specification, our distance dummy took a value of 1 if the set was made near to the MPA and 0 otherwise. Here we define our distance dummy to be the number of miles away from the MPA border that a set takes place. We set the total fishing ground to extend 400 miles away from PMNM.

Defining our distance variable using continuous distance reverses the interpretation of the diff-in-diff coefficient. Recall, the diff-in-diff coefficient is defined as $ExpansionDummy * DistDummy$; in the continuous-distance specification, the β_3 coefficient measures the effect of fishing further away from the MPA border, after the MPA was expanded. Thus, a *negative* β_3 value indicates relative CPUE will increase as miles from MPA border decreases, suggesting a positive biological spillover.

We present the results for the continuous distance specification in the same format as our region-radii models. Figure 1.5 displays the diff-in-diff coefficient for bigeye, yellowfin, all,

and the other species groups. Results remain consistent across specifications where yellowfin has the largest, statistically significant spillover effect. The spillover for bigeye is smaller in magnitude than that of yellowfin, but, when compared to previous region-radii models, these estimates are stronger in statistical significance across all specifications. A spillover effect for all species caught still remains inconclusive. Table 1.3 presents the "Kitchen Sink" specification for the continuous distance specification. Additional tables can be found in the Appendix.

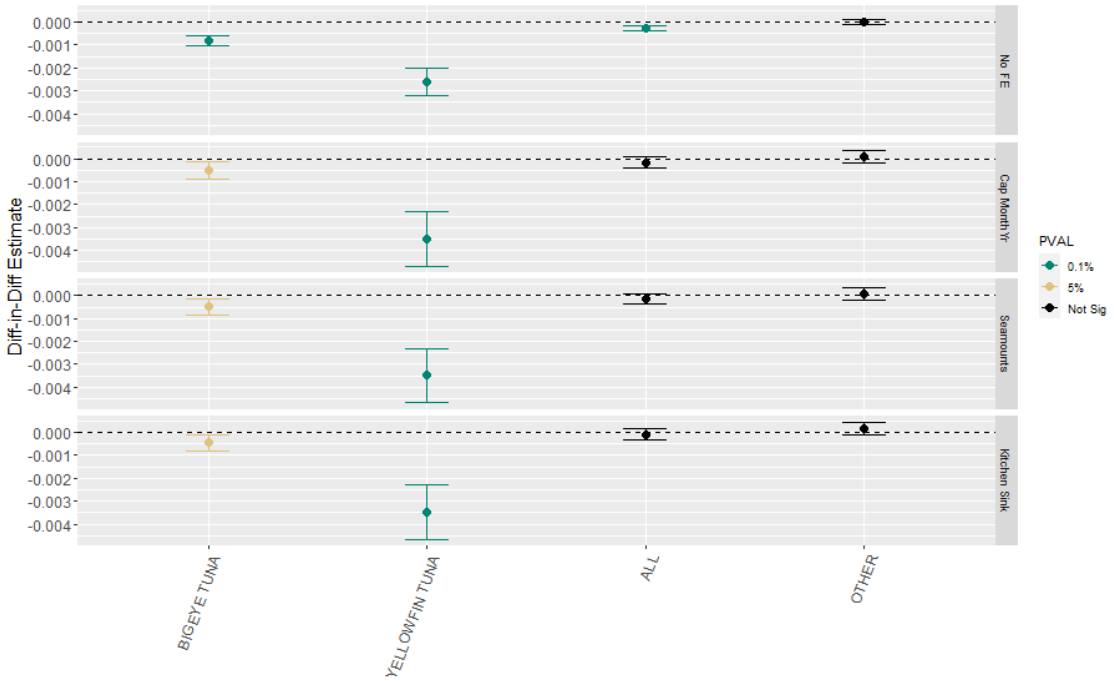

Figure 1.5: Continuous Distance: The following quantiles describe fishing distribution relative to PMNM boarder: 25% of fishing sets were made 129.8 miles from PMNM, 50% of fishing sets were made 234.0 miles from PMNM, 75% of fishing sets were made 313.7 from PMNM.

Table 1.3: Kitchen Sink (Continuous Distance): Our distance variable is defined as 'miles away from MPA boarder'. Heterogeneity across captain efficiency, natural time trends, seamount sets, and various gear are controlled for. Each successive column displays results for each species group Bigeye, Yellowfin, All, and Other, using a difference-in-difference regression. DID coefficients measure the effect of fishing further away from PMNM after PMNM was expanded in the 2016. The sample runs from January 6, 2010 to January 11, 2020. *p<0.1; **p<0.05; ***p<0.01 Heteroskedasticity-robust standard errors presented in parentheses.

	Bigeye	Yellowfin	All	Other
	(1)	(2)	(3)	(4)
Diff in Diff	-0.0004^{**}	-0.003^{***}	-0.0001	0.0002
	(0.0002)	(0.001)	(0.0001)	(0.0002)
Expansion Dummy	-0.213^{***}	-2.061^{***}	-0.366^{***}	-0.316^{***}
	(0.065)	(0.652)	(0.058)	(0.107)
Distance Dummy	0.0003^{**}	-0.001^{***}	-0.0001	-0.0002^{*}
	(0.0001)	(0.0003)	(0.0001)	(0.0001)
Observations	16,311	16,311	16,311	16,308
R^2	0.119	0.137	0.136	0.130

1.5 Conclusion

No-take marine protected areas have been a focal point of the fisheries and marine conservation literature. An extensive amount of research has gone into estimating the economic and conservation benefits of MPAs. Despite this effort, there is still debate about whether the benefits of MPAs exceed the costs. The contribution of this paper is to help quantify the unintended spillover benefits of one of the world's largest MPAs, Papahānamokuākea. By using a difference-in-differences framework with vessel fixed effects, we control for unobserved heterogeneity across space, time, and vessels to derive an unbiased estimate of spillover benefits.

The expansion of Papahānamokuākea occurred fairly recently in 2016. Considering bigeye and yellowfin have a life expectancy of around seven years and reach reproductive maturity at age two or three[2], enough time may not have elapsed for a hypothetical biological

[2]https://www.fisheries.noaa.gov/species/pacific-bigeye-tuna

benefit to accumulate. Nonetheless, we observe spillover benefits for bigeye and yellowfin, the two main target species of the deep-set fishery. Our findings consistently estimate a statistically significant spillover for yellowfin and a weakly positive spillover for bigeye tuna.

The varying benefit across tuna species could be explained by the tendency for yellowfin to be more resident in the Hawaiian archipelago than bigeye. Yellowfin originating from near-shore nurseries have been observed to linger in neighboring areas around the Hawaiian Islands (Wells et al., 2012; Rooker et al., 2016). Unlike yellowfin, bigeye are much more migratory, making a spillover effect less likely[3]. In addition, it is perhaps not surprising that the estimates of our all-species models were weakly positive or, in some cases, inconclusive because positive benefits for one species might be offset by negative spillover for another, especially if there are predator-prey or resource competition interactions. Though the evidence of a positive spillover is small in magnitude, this framework provides a basis for quantifying the spillover benefits of a large marine protected area.

https://www.fisheries.noaa.gov/species/pacific-yellowfin-tuna

[3]http://www.wpcouncil.org/wp-content/uploads/2014/11/Final-Bigeye-Workshop-Report.pdf

Chapter 2

Testing the Pollution Haven Hypothesis on the High Seas

2.1 Introduction

"Testing the pollution haven hypothesis is an exercise in policy evaluation. We are trying to compare what we observe in the world regarding trade flows or pollution levels under one set of trade and pollution policies, with the unobserved counterfactual created when these policies are different. The key empirical problem is that we do not observe the counterfactual." - Taylor (2004)

Fishing is a production process that uses natural resources, labor, and highly mobile capital as inputs. This process produces market goods (fish) and externalities (resource depletion, unintentional killing of birds, turtles, and dolphins, plastic pollution[1], etc.). The mobility of capital in fishing is fundamentally a consequence of the mobility of the natural resource inputs but this mobility also makes fishing an ideal setting for studying how regulations affect the spatial deployment of labor and capital.

The Pollution Haven Hypothesis (referred to in more modern literature as "leakage") is "the idea that polluting industries will relocate to jurisdictions with less stringent environmental regulations" (Levinson, 2008). In an extreme version of the hypothesis (with few barriers to trade and more polluting technologies being used outside the regulated region), environmental regulation can increase aggregate pollution. The hypothesis emerged

[1] See Uhrin et al. (2020) and Lebreton et al. (2018)

as a major issue in the international (and environmental) economics literature around the time of the policy debate over the impacts of the 1994 North American Free Trade Agreement (NAFTA). It has been described as "one of the most contentious and hotly debated predictions in all of international economics" (Taylor, 2004). There have been over 10,000 publications to date on the topic with some of the most influential including Grossman and Krueger (1991), Copeland and Taylor (1994), and Levinson and Taylor (2008). A lot of the early literature was linked to the idea of the Environmental Kuznets Curve.[2] More recent work has tended to use the term leakage but the principles are much the same: see Fowlie et al. (2016), Fowlie and Reguant (2018), and Fowlie and Reguant (2020).

Despite a large theoretical literature and a relatively intuitive explanation for why the hypothesis might be observed in the real world, causal evidence has remained elusive. Levinson (2008) points out that regulatory stringency and pollution are determined simultaneously. Taylor (2004) draws attention to the endogeneity of both trade and pollution policy and more recent work by Millimet and Roy (2016) blame the inconclusive nature of the empirical literature on the lack of a credible instrumental variable for regulation and a failure to account for geographic spillovers.

Fishing on the high seas in the Pacific Ocean provides a unique setting to perform a causal test of the Pollution Haven Hypothesis. In the next section, we expand in more detail on the industry and its regulatory environment but some of the key features include the following. Regulatory stringency is largely determined by environmental factors: in some years fishing of bigeye tuna is restricted and in some years it is not. The timing of regulation is also randomly determined. Further, trade policy is held fixed while environmental regulation is varying. Critically, some firms are regulated and some are not, allowing for the observation of counterfactual behavior and the elimination of geographic spillover concerns. And finally, as mentioned before, capital is highly mobile, allowing for a rapid and clear response to new regulations.

As a preview of our results, double- and triple-difference tests on changes in daily production decisions provide causal evidence in support of the pollution haven hypothesis. Firms

[2]There is a also a strand of the literature that explores a variant of the hypothesis: countries actually compete to lower their environmental standards in order to attract FDI ("environmental dumping"). See **?**.

relocate over 600 miles within a few weeks of new regulatory measures. We do not observe reductions in aggregate environmental damage and, in some years, more stringent regulations cause more environmental harm than would be observed in the absence of these regulations.

2.2 Background on Tuna Fishing and Regulations

Tuna fishing contributes over $40 billion to the global economy. Tuna species are wide-ranging throughout the world's oceans and are some of the most migratory fish species on the planet. Bigeye tuna (*Thunnus obesus*) have been recorded migrating over 5,800 miles in a single year (the equivalent of swimming from Tokyo to Los Angeles) and some Bluefin tuna (*Thunnus thynnus*) have been documented covering 25,000 miles in less than two years. The fishery we study targets bigeye tuna, not bluefin.

Longline tuna fishing in Hawaii consists of 150 vessels (some owned by the same firms) with annual landings around $100 million and an associated economic impact of $200-300 million. The main tuna species landed are bigeye and yellowfin tuna. Most bigeye tuna are caught on the high seas, beyond the sovereign resource claims of coastal nations. As a result, regulations are set by voluntary international agreements.[3]

The most important international organizations for the management of tunas and tuna-like species in the Pacific are the Inter-American Tropical Tuna Commission (IATTC), established in 1949, and the Commission for the Conservation and Management of Highly Migratory Fish Stocks in the Western and Central Pacific Ocean (WCPFC), established in 2004. Although country membership is voluntary for both the WCPFC and IATTC, members are legally obligated to implement all resolutions of the commissions. Currently, the IATTC has 21 members and 4 cooperating non-members; the WCPFC has 26 members and 7 participating territories (see Figure (2.1)). Importantly, each U.S. territory in the Pacific is treated as an independent entity for the purposes of management. So, in a way, American Samoa and other US territories are considered separate parties to these agreements from the

[3]Based on the 1982 UNCLOS, ratified by 160 countries, fish that are located within 200 nautical miles of a country's coastline are recognized as the property of that nation. These 200 nautical mile zones are referred to as Exclusive Economic Zones (EEZs). Any fish that exist beyond the boundaries of these zones are not recognized, under international law, as belonging to any particular sovereign nation. As a result, voluntary international agreements have emerged over time to attempt to manage populations of fish that exist beyond EEZs. 1 nautical mile is equivalent to 1.15 international miles.

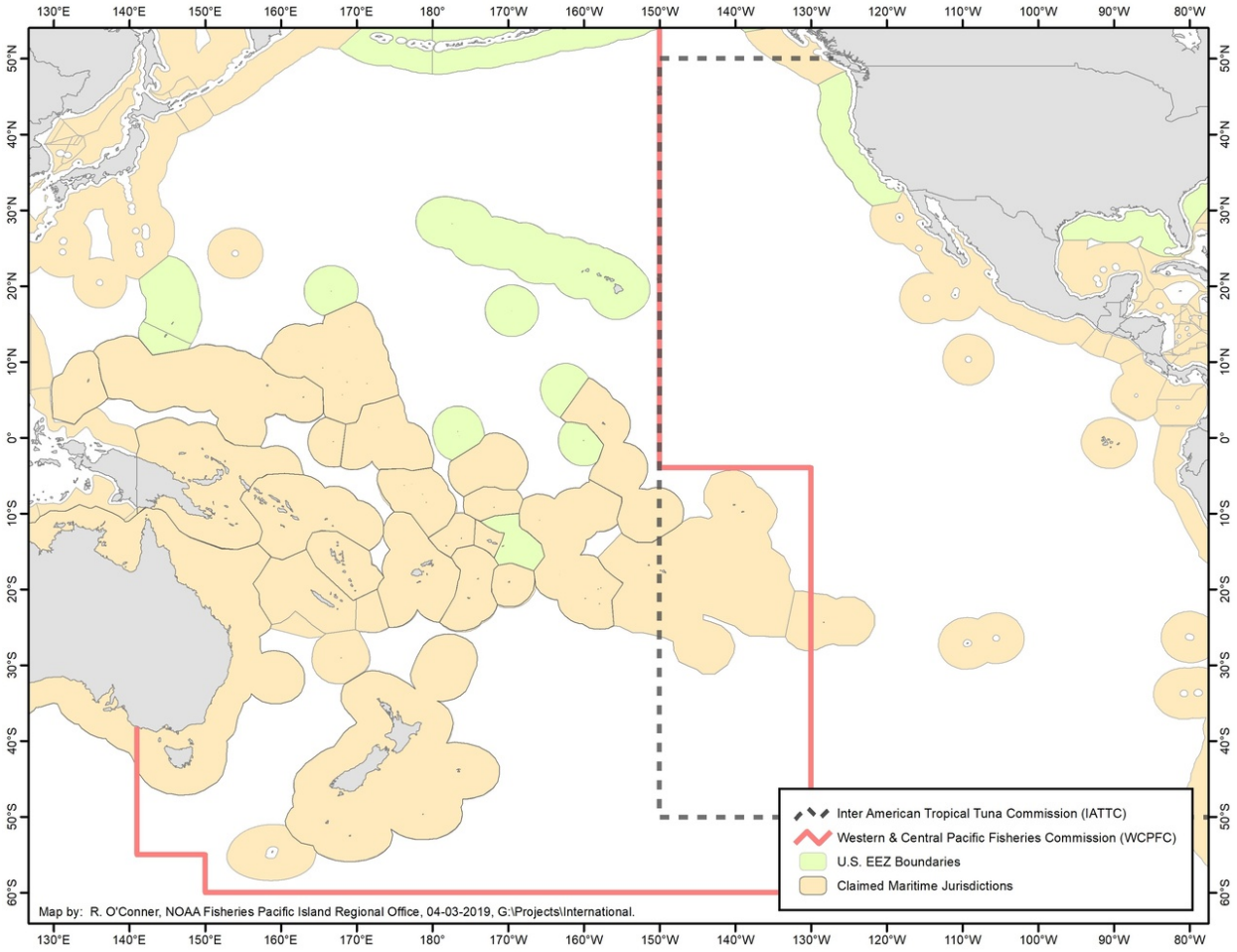

Figure 2.1: Map showing the Pacific Ocean and the regulatory jurisdictions of the IATTC and the WCPFC. US sovereign waters are shaded in green. Most US longline fishing takes place to the north of the Hawaiian island chain. Source: NOAA.

United States of America (which includes Hawaii).

From a regulatory perspective, the Pacific Ocean is split at 150° W longitude, with the IATTC regulating the eastern side and the WCPFC regulating the western side (Figure (2.1)).[4] Each commission is responsible for the conservation and management of tunas and tuna-like species in its respective area (called "Convention" areas, based on the international conventions that established the commissions).

One of the species managed by IATTC and WCPFC is bigeye tuna. Bigeye is one of the larger tuna species (common length is 1.8m) and ranges throughout the Atlantic, Indian and Pacific Oceans. The current scientific consensus is that bigeye tuna in the Pacific Ocean constitute a single population (Wu et al. (2014); Rooker et al. (2016); Adam et al.

[4]The IATTC and WCPFC convention areas overlap within a rectangular area bounded by 50° S. latitude, 4° S latitude, 150° W longitude, and 130° W longitude; however, for purposes of this study, this overlapping area is irrelevant because the fishery of interest does not operate this far south.

(2003); Musyl et al. (2003); Abascal et al. (2018); Schaefer et al. (2015)). Thus, bigeye tuna represents a true global commons and the IATTC and the WCPFC attempt to regulate the same population of fish that migrates across the boundary of their respective convention areas.

Each commission adopts resolutions pertaining to the management of bigeye tuna in its own convention area each year. The most important resolution for this analysis sets annual catch limits, which define the maximum amount of bigeye tuna that each member country or territory may land in a calendar year. Once this limit is reached, no additional bigeye tuna may be kept by regulated vessels in that convention area. These limits are set based on stock assessments and scientific consensus on sustainable catch.

Catch limits have applied to U.S.-permitted longline vessels in the Western and Central Pacific since 2009 (50.CFR.300.224) and in the Eastern Pacific since 2004 (50.CFR.300.25). Based on the commissions' resolutions, the U.S. National Marine Fisheries Service establishes a calendar year catch limit (measured in metric tons) for the amount of bigeye tuna that can be caught by longline vessels. Once this limit is reached, certain fishing prohibitions go in to effect for the remainder of the calendar year, with some exceptions that are critical to our identification strategy and are discussed later. For both the WCPFC and IATTC convention areas, the following prohibitions apply: 1) vessels may not retain on board, transship, or land bigeye tuna caught by longline gear in the convention area, 2) bigeye tuna caught in the convention area that are already on board the vessel when prohibitions are implemented must be brought to shore within 14 days, 3) vessels may not fish with longline gear both inside and outside the convention area on the same fishing trip, 4) if a vessel is inside the convention area, all gear must be stowed so that it is not immediately available for fishing, and 5) bigeye caught in the convention area may not be transshipped to another fishing vessel. The period in which these prohibitions are in effect are generally referred to as fishery "closures."

There are several important exceptions to these rules. For the WCPFC convention area, bigeye tuna that meet at least one of the following criteria do not count against the U.S. fishing limit, and are therefore exempt from prohibitions during closures: 1) bigeye tuna that is caught in the convention area (but outside of the U.S. EEZ surrounding the Hawaiian

Archipelago) and landed in a U.S. territory with a valid permit, 2) bigeye tuna caught in the convention area (but outside of the U.S. EEZ surrounding the Hawaiian Archipelago) by a vessel that is permitted to fish in both American Samoa and Hawaii (i.e. a "dual-permitted" vessel), and 3) bigeye tuna that is "attributed" to an American territory under a specific transfer agreement. This third exception is authorized under the Consolidated and Further Continuing Appropriations Act (CFCAA), passed in 2011, which allows Hawaii longliners to negotiate a payment to a sustainable fisheries fund in a U.S. territory in return for a transfer of some of that territory's fishing limit. Finally, for the IATTC convention area, all vessels smaller than 24 m in length are exempt from prohibitions. This is the majority of vessels, meaning that IATTC closures have minimal impact on total fishing effort. See Table 2.1 for a summary of the number of vessels subject to IATTC closures. The term "effective closure" is used by fisheries managers and in the literature to refer to periods when both the WCPFC and IATTC areas are concurrently closed (Ayers et al., 2018). This implies that a relatively small subset of US vessels prevented from catching bigeye tuna anywhere in the Pacific Ocean.

There have been multiple effective closures for bigeye tuna in the United States since the initial adoption of catch limits (Figure (2.2)). The WCPFC convention area closed in 2009 and 2010, respectively. Although the U.S. reached its catch limit in each year from 2011 to 2014, territorial transfers under the CFCAA prevented an effective closure. From 2015 to 2017, there were temporary closures while the terms of territorial transfers were being negotiated and implemented. The IATTC convention area has closed each year from 2004 through 2006 and 2013 through 2017. Each closure remained in effect through the end of the calendar year, except in 2016, when the fishery reopened due to a miscalculation of prior catch. Again, the WCPFC closures never apply to dual-permitted vessels and the IATTC closures never apply to vessels less than 24 m long, so there are always some vessels that can keep fishing regardless.

Unlike most other regulatory settings, the severity of environmental regulations in the tuna fishing industry are largely determined by environmental factors. Although bigeye catch is obviously endogenously determined by fishing activity, the biggest determinant of whether the cap is reached in any given year is environmental conditions, particularly ocean

temperature. Variation in ocean temperature affects tuna reproduction which does not manifest itself until 2 to 3 years later when juveniles mature to catchable size. Likewise, in any given year, variation in ocean temperature affects where tuna locate within the Pacific Ocean and thus their vulnerability to capture.

This regulatory and ecological context provides quasi-random assignment of regulations to firms over time and space. In a given year there may be no closures, a partial closure (representing one side of the Pacific Ocean closed, but not the other), or a complete closure (both sides closed). In addition, the start date and duration of this closure varies from year to year. Contrast this setting with pollution regulation: the sulfur dioxide emitted from a coal-fired power plant's chimney does not randomly vary from year to year based on current and lagged weather. Obviously the dispersion of that pollution is affected by current weather but the stringency of environmental regulations is typically based on what is emitted, not on where the pollution ends up.

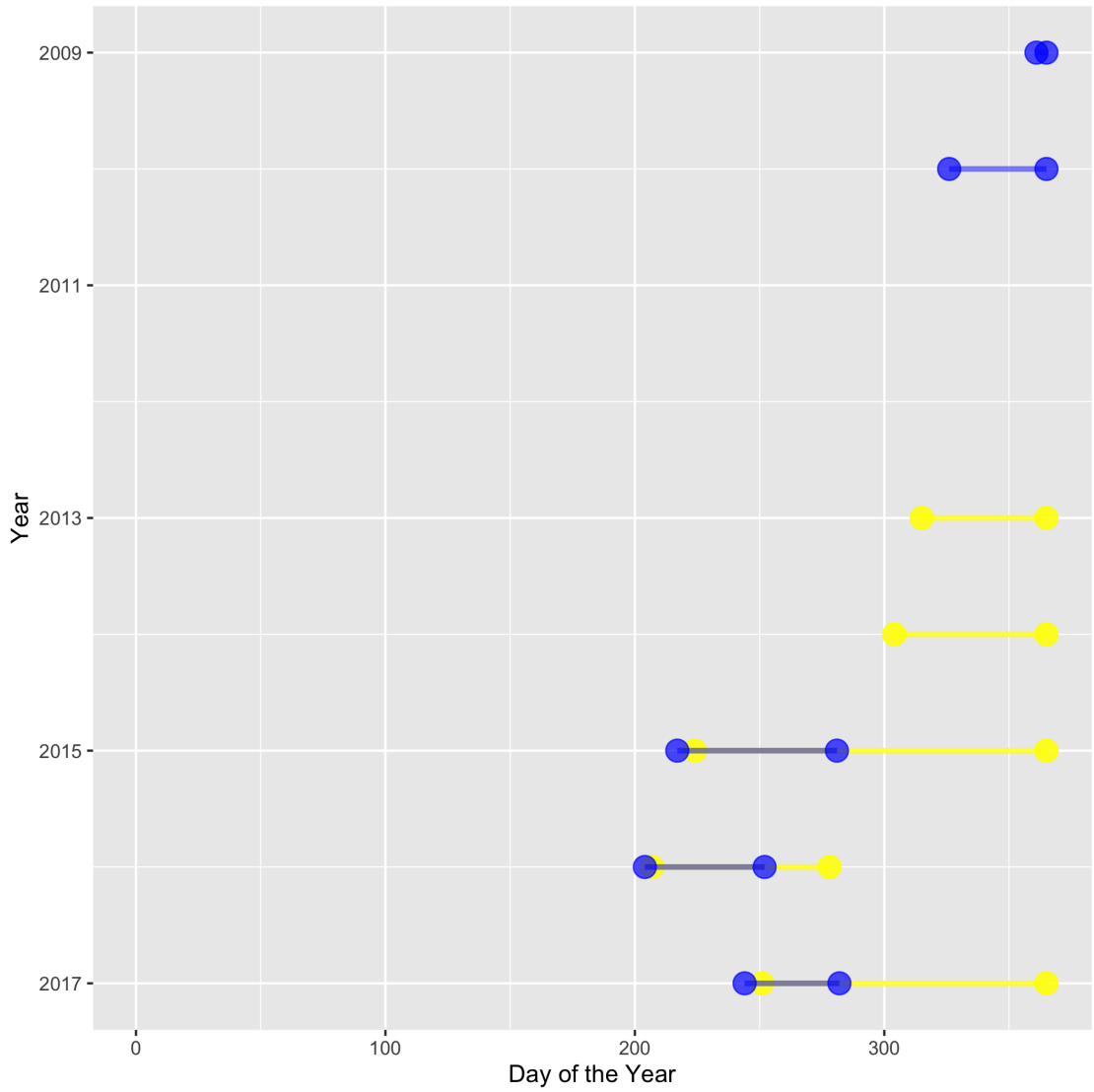

Figure 2.2: Timing of Eastern and Western Pacific Closures. Yellow lines indicate Eastern Closures. Blue lines indicate Western Closures. Day 1 of the year is January 1st, Day 2 is January 2nd, etc.

Table 2.1: Number of Vessels in Each Subgroup in 2016

	Less than 24m (exempt from IATTC)	Greater than 24m
Dual-permitted (exempt from WCPFC)	15 vessels	9 vessels
Single-permitted	95 vessels	26 vessels

2.3 Data Visualization of Firm Responses

2.3.1 Data

In 1990, the National Marine Fishery Service (NMFS) initiated a Hawaii Longline Limited Entry Permit program in which a permit was required for all vessels using longline gear to catch pelagic species within Hawaii's EEZ or any vessels who land their catch in a Hawaiian port.[5] As part of the program, all captains were federally mandated to self-report all fishing activity in the form of logbooks. These logbooks must be submitted to the National Oceanic Atmospheric Administration (NOAA) within 72 hours of returning to port.

The logbook data details trip characteristics such as jurisdiction for which the permit was issued, each fishing set location, total species caught per fishing set, date of trip departure, and date of trip arrival. Single permitted American Samoa vessels and California vessels can occasionally show up in this data set, but we only focus on Hawaii permitted vessels (dual or single) and filter out all other observations. Depending how fishing gear is arranged, longline vessels will either target bigeye tuna or swordfish. We filter out any observation in which swordfish was the target species and only consider sets targeting bigeye. If a set was made with the intention of catching bigeye but was unsuccessful, we report a catch of zero.

2.3.2 Visualizations

We classify four different fishery subgroups based upon the level of regulatory exposure for each closure type: dual permitted & less than 24 meters (Dual/<24), dual permitted & greater than 24 meters (Dual/>24), single permitted & less than 24 meters (Sngl/<24), and single permitted & greater than 24 meters (Sngl/>24). See Table 2.1 for the numbers in each subgroup in 2016 (these do not vary much from year to year). Each of these subgroups are exposed to a different treatment effect when a closure commences and, in theory, will have a different response. Based on the regulatory structure, the Dual/<24 group will be in the most advantageous position; neither a western nor an eastern closure should alter their fishing activity. Dual/>24 vessels will be the second most advantageous group. These vessels will be limited to the Western Pacific during an Eastern Pacific closure but since most

[5] https://www.fisheries.noaa.gov/permit/hawaii-longline-limited-entry-permit

fishing activity occurs there anyway, we hypothesize a slight to negligible effect on fishing activity. The Sngl/<24 group will be negatively impacted by a Western Pacific closure but will be left unaffected by an eastern closure. When the WCPFC quota is reached, this fishery subgroup will only be allowed to operate in the Eastern Pacific, resulting in higher operational costs and longer fishing trips. The last fishery subgroup, Sngl/>24, is the most impacted group and are negatively impacted by both a WCPFC and an IATTC closure. When both sides of the Pacific experience a closure, fishing for bigeye tuna for this group must come to a complete halt.

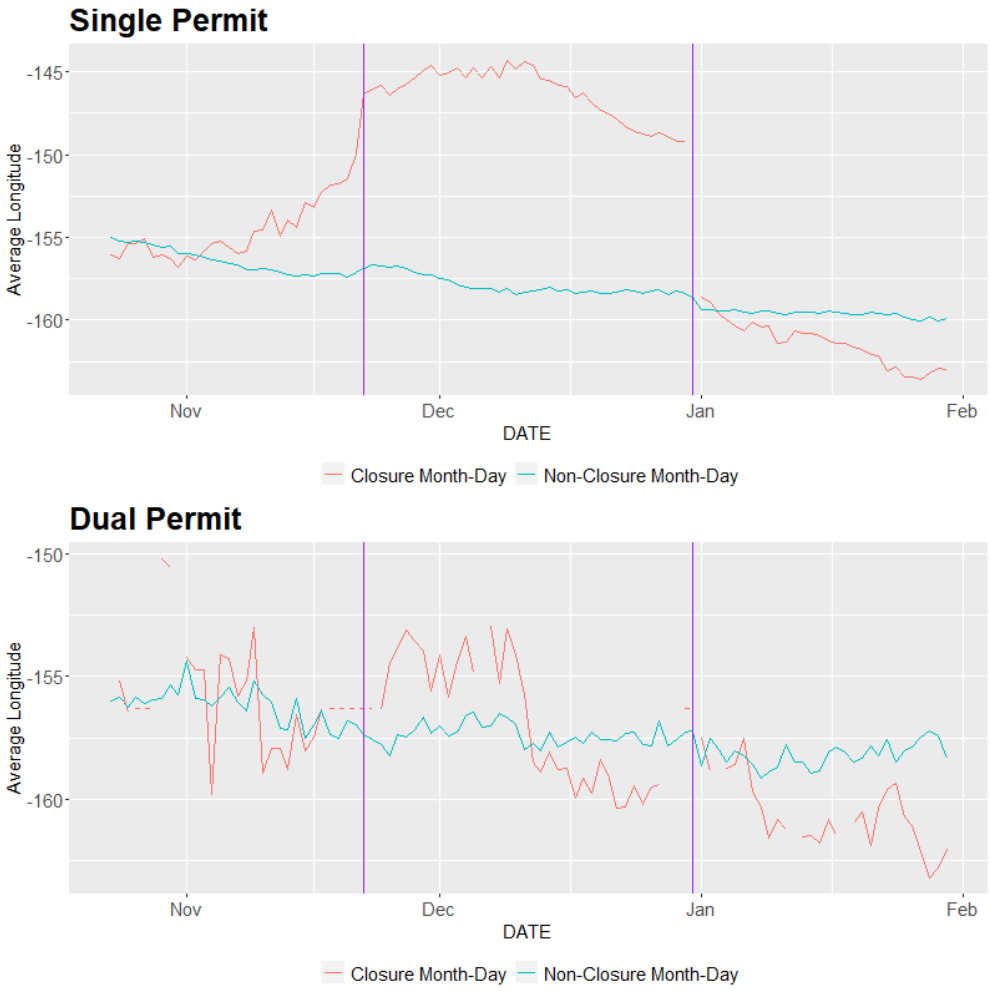

Figure 2.3: Comparing of Set Longitude Between Closure and Non-Closure Years: Red time trends depict set location during the 2010 western closure and blue time trends depict average set location for the same month-day combination for all other non-closure years. The top panel shows single permit vessels (treated) and the bottom panel shows dual permitted vessels (control).

Quota regulations vary across time, space, and individual vessels. If captains adjust behavior to sustain fishing operations during a closure, economic theory would predict effort will be concentrated in less regulated areas. When the WCPFC experiences a closure, single permitted vessels will migrate east. Likewise, when an IATTC closure commences, vessels measuring greater than 24 meters in length will shift their effort to the western Pacific. We start by examining the 2010 Western closure. The was the first closure of any significant duration; the 2009 Western closure only lasted for a couple of days. Figure (2.3) draws comparisons between set locations across fishery subgroups and across time. Longitude of set locations for the single permitted group (Sngl/<24 and Sngl/>24 vessels) are shown in the top panel (these are vessels impacted by the closure)and set longitude for the dual permitted group (Dual/<24 and Dual/>24 vessels) are shown in the bottom panel (these are vessels that are not directly affected by the closure). Time trends during a closure year are plotted in red while the average set longitude for the same month-day combination in all other non-closure years is plotted in blue. Once the 2010 western closure starts, the location of sets made by the dual permitted group fluctuates around the non-closure years line but follows a similar trend to non-closure years, i.e. there is no major East-West movement. However, once the closure begins the location of the single permitted group dramatically shifts to the east (approx. -145°), as shown by an increase in longitude values. Depending on latitude, moving from -157° to -145° is equivalent to traveling between 550-850 miles to the east.

Figure 2.4: Comparing Fishing Conditions For the 2016 Western Closure: All time series include fishing activities 30 days pre and 30 days post closure start and end respectively. Left panel represents longitude relative to HNL port and the right panel represents catch. During a western closure, treated groups are single permitted vessels, control groups are dual permitted vessels.

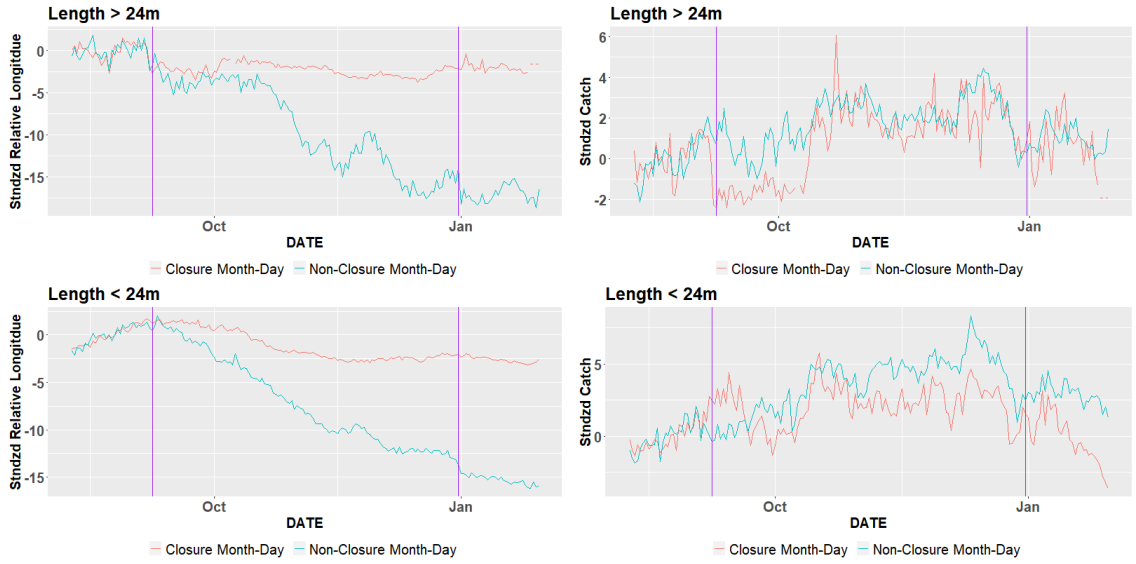

Figure 2.5: Comparing Fishing Conditions For the 2017 Eastern Closure: All time series include fishing activities 30 days pre and 30 days post closure start and end respectively. Left panel represents longitude relative to HNL port and the right panel represents catch. During an eastern closure, treated groups are vessels larger than 24m in length, control groups are vessels shorter than 24m in length.

To obtain a better understanding of recent fishing behavior during a closure, Figure (2.4) and (2.5) present a visual comparison of fishing activity during the 2016 western and 2017 eastern closure to a typical 'business as usual', non-closure year. Fishing activity is defined in two ways. First, we calculate aggregate daily catch. Second, we take the daily average longitude relative to Honolulu (HNL) port by applying the follow differencing: *Set Longitude − HNL longitude*. Each relative longitude value can be interpreted as the number of degrees east of the prime meridian relative to HNL port. Time series are plotted 30 days prior to a specific closure start date and 30 days post the closure end date. For comparison, we also plot fishing activity that occurs during the same calendar day in all other, non-closure years. If calendar day t_y in another year was a closure day, activity from day t_y would not be included in the non-closure time series. All data is standardized based off the pre-closure mean and the pre-closure standard deviation such that each point can be interpreted as the number of standard deviations away from the pre-closure average.

Ideally, we would make this comparison for each subgroup of the fishery but due to confidentiality of the NMFS data sets, any fishing days in which fishing activity involving three vessels or less must be removed from all visualizations. To construct a more complete time series, we conditionally fill in confidential days by applying the following rule: if the number of unique permits across all confidential days is greater than three, we average fishing activity across all confidential days and report the average value in the time series. Applying this conditional requirement leaves the time series interpretation as such: solid lines indicate raw values, horizontal dashed lines indicate the average values for days that would have otherwise been confidential, and discontinuities in the time series indicate days that did not meet the conditional requirement and must remain confidential (for the purposes of visualization only, this data is included in our regression analysis).

The 2016 western closure lasted 48 days, most of which occurred simultaneously with an eastern closure. Figure 2.4 presents comparisons for the western closure. The red lines represent either daily average longitude relative to Honolulu port or total daily catch. The blue line represents relative average daily longitude and average daily catch in all other, non-closure years. Dual permitted vessels are exempt from western quota restrictions and continue "business as usual" fishing activity before and during the 2016 closure and across

closure and non-closure years. However, sets made by the single permitted group are displaced east for most of the closure, given by the increase in set longitude values, yet catch remains relatively constant at its pre-closure mean.

An eastern closure is expected to have a smaller impact on the Hawaiian longline fishery relative to western closures because most vessels historically fish closer to the Hawaiian Islands and most are exempt from these closures anyway. When an eastern closure commences, larger vessels (>24 meters) are prohibited from fishing past -150° longitude and must stay strictly in the western side of the Pacific. We present fishing activity for vessels over 24 meters in length (treated group) and for vessels under 24 meters in length (control group) in Figure 2.5. Both subgroups continue to fish closer to the Hawaiian islands during the closure relative to non-closure years. Despite the eastern closure being in effect, catch during this closure is not significantly different from all other non-closure years.

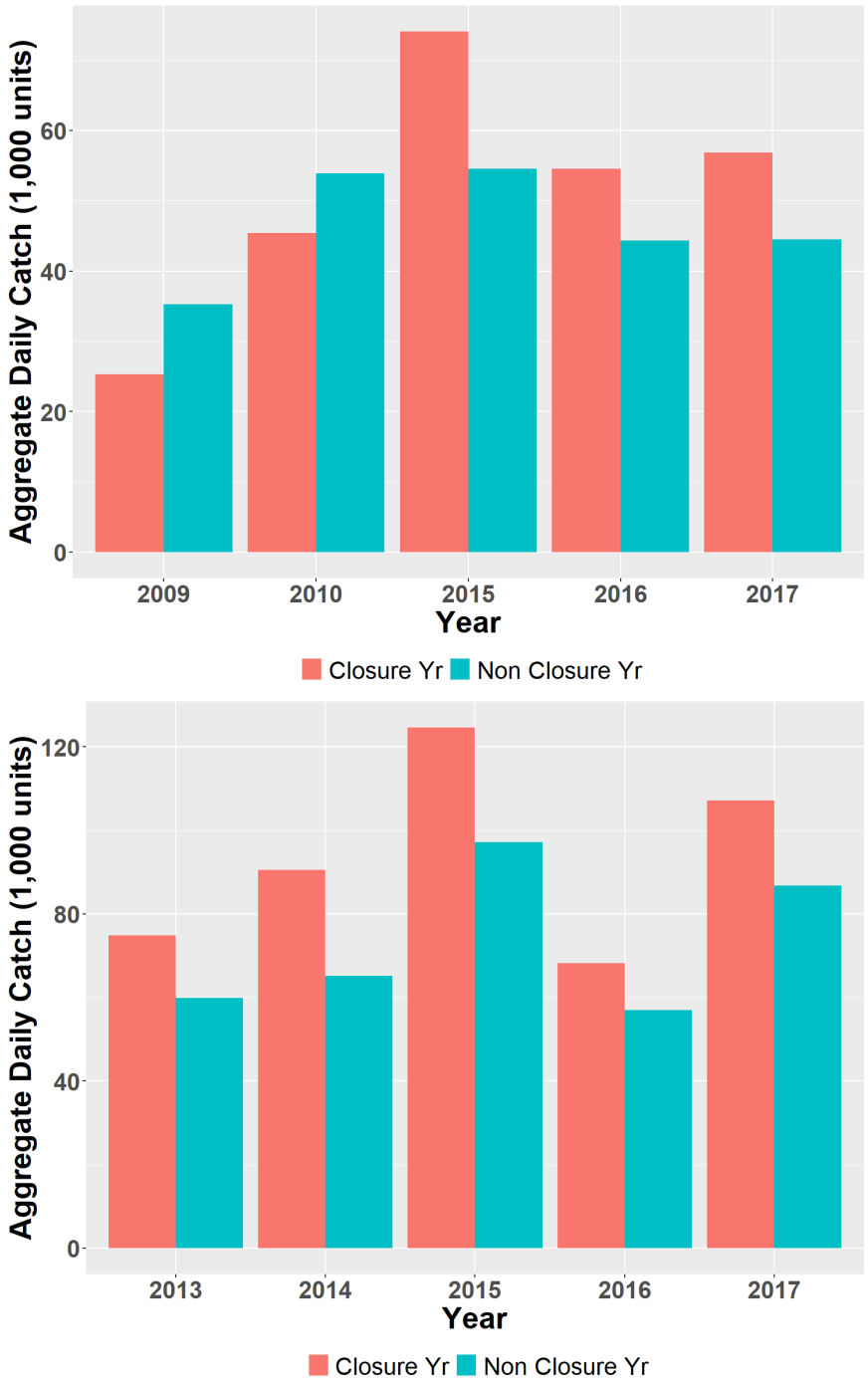

Figure 2.6: Comparing Average Daily Catch Across Years: Aggregate catch during closure years compared to average yearly aggregate catch for the same month-days in all other, non-closure years.

The main purpose of a closure is to mitigate against species depletion. If catch decreases because of an enforced closure, the closure is successful in achieving its goal. To quantify this, we calculate total catch across all closure days within a closure year and compare it to the average total catch across the same month-days combinations, in all other non-closure years (Figure 2.6). The pink bar represents average daily total catch across the closure days and the blue bar represents average daily total catch for the same month-days across all other, non-closure years. The earliest western closures appear to be successful at lowering catch. For subsequent western closures and for all eastern closures, daily total catch is higher during a closure year compared to the average for that time period in all other non-closure years. It is important to note, these bar graphs do not account for other factors which might influence catch (which we will attempt to control for in our regression analysis).

2.4 Identification Strategy

To control for endogeneity concerns, we utilize a difference in differences (DID) model. The basic idea is to calculate the difference in fishing activity between each group before and after the policy intervention and then conduct a final differencing of the differences to obtain an estimate of the effect of the policy on each group. When executed correctly, this should eliminate potential temporal and cross-sectional biases. We formulate three different DID specifications: Temporal DID, Within-Year DID, and Triple Differences DID.

Temporal Approach

The first approach exploits the fact that closures occur in some years and not others, as well as the fact that the timing of closures varies within closure years. We define our treatment group and control groups based on the visualized comparison presented in the previous subsection. We restrict our data set to each month-day combination that takes place 30 days prior to the closure-start date and 30 days post the closure-end date. Within each fishery subgroup, we assign fishing activity during a closure year to being "treated" and assign fishing activity from the same month-day combinations for all other non-closure years to being "control" days (Equation 2.1). Our outcome variable, $Dep_{i,t,y}$ represents fishing activity (catch and longitude) for each set i, on month-day d, in year y. Our $TreatmentYear_y$

represents our treatment dummy by assigning a value of 1 if $y = Y$ where Y is the closure year, and 0 otherwise. The indicator variable $MonthDay_d$ will act as our time treatment by taking a value of 1 for all $d > D$ where D is the month-day of the closure-start date, and 0 otherwise. The DID coefficient is then represented by the last term, $TreatmentYear_y * MonthDay_d$, leaving β_3 as our DID estimator.

$$\begin{aligned} Dep_{i,t,y} = \beta_0 + \beta_1 TreatmentYear_y + \beta_2 MonthDay_d \\ +\beta_3(TreatmentYear_y * MonthDay_d) + \epsilon_{i,t,y} \end{aligned} \tag{2.1}$$

Within Year Approach

We take a more classical approach at difference in difference estimation using the Within-Year DID, refer to Equation (2.2). We identify treatment and control group based off the regulatory structure of each closure. For western closures, our treatment group will be all single permitted vessels. For eastern closures our treatment group will be all vessels measuring greater than 24 meters in length. Each dependent variable, $Dep_{i,g,t}$, is taken from set i, by group g, taken on date t. $TreatmentGroup_g$ takes a value of 1 if set i was made by a vessel in the treated group, and 0 otherwise. $Date_t$ takes a value of 1 if $t \; \epsilon \; \mathbf{T}$ where $\mathbf{T}$ is a vector of closure dates, and 0 otherwise. Our estimate of interest is then β_3.

$$\begin{aligned} Dep_{i,g,t} = \beta_0 + \beta_1 TreatmentGroup_g + \beta_2 Date_t \\ +\beta_3(TreatmentGroup_g * Date_t) + \epsilon_{i,g,t} \end{aligned} \tag{2.2}$$

Triple Difference Approach

Our last identification strategy leverages all three sources of policy induced variation which occurs across fishery subgroups, across years, and across calendar days. For each dependent variable (catch/ longitude) from set i, by a vessel in group g, on month-day d, in year y, we estimate the effects of a closure by running a triple difference in difference model, refer to Equation (2.3). As defined earlier, the $TreatmentGroup_g$ takes a value of 1

if the set was made by a vessel in the treated group and 0 otherwise. For western closures, all single permitted vessels will be flagged, for eastern, all large vessels (over 24 meters) will be flagged, and for an effective closure, all large single permitted vessels will be flagged. The $Monthday_d$ dummy variable will take a value of 1 if time d falls on each month-day combination in a specific closure and 0 otherwise. The $TreatmentYear_y$ dummy will take a value of 1 if y equals the year of the closure. Our variable of interest will be β_7, which will measure the closure effects on the vessels within a treated group, fishing during the same month-day as the closure, within the closure year.

$$\begin{aligned} Dep_{i,g,t,y} = \beta_0 + \beta_1 TreatmentGroup_g + \beta_2 MonthDay_d + \beta_3 TreatmentYear_y \\ +\beta_4(TreatmentGroup_g * TreatmentMonthday_d) \\ +\beta_5(TreatmentGroup_g * TreatmentYear_y) \\ +\beta_6(TreatmentYear_y * TreatmentMonthday_d) \\ +\beta_3(TreatmentGroup_g * TreatmentMonthday_d * TreatmentYear_y) + \epsilon_{i,g,t,y} \end{aligned} \tag{2.3}$$

2.5 Selected Results

2.5.1 Western and Eastern Closures

We run our three models on the western 2016 and eastern 2017 closures. The Temporal DID Results are presented for longitude in Tables (2.2) and (2.4), and results for catch are presented in Tables (2.3) and (2.5), for the western and eastern closure respectively. Each column represents the four fishery subgroups. The DID coefficient is displayed on the bottom row of each table. Based on the regulatory structure, the single permitted vessels should be most affected during a western closure and the larger vessels (>24 meters) should be most affected by an eastern closure.

During the 2016 western closure, there was a statistically significant effect on location of sets, pushing the Dual/<24 and the Sngl/<24 groups more east, as interpreted by the positive DID coefficient. The negative coefficient on longitude for the Sngl/>24 vessels can

be explained by captains exiting the market completely, refer to Table (2.2). Despite the western closure being in effect, Table (2.3) reports a positive coefficient on catch for the Sngl/<24 group.

The early part of the 2017 IATTC closure was accompanied by a WCPFC closure but the Western Pacific closure ended much earlier than the east. During the eastern closure in 2017, we see a negative effect on longitude across all fishery subgroups indicating vessels tend to keep their western position, refer to Table (2.4). Despite restrictions, catch increases across all fishery subgroups.

Table 2.2: Temporal DID (West 2016 Closure) Longitude Relative to HNL: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	−1.751***	−4.939***	3.729***	−0.317*
	(0.292)	(0.721)	(0.132)	(0.184)
Closure Month−Day	0.477***	−0.511	0.703***	0.682***
	(0.159)	(0.377)	(0.048)	(0.094)
Diff in Diff	2.458***	0.316	7.405***	−2.516***
	(0.437)	(0.821)	(0.154)	(0.703)
Observations	8,686	1,867	92,082	24,866
R^2	0.007	0.081	0.090	0.003

Table 2.3: Temporal DID (West 2016 Closure) Catch: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	−0.718*	0.755	1.132***	0.488
	(0.385)	(0.880)	(0.166)	(0.321)
Closure Month−Day	−0.257	0.152	−0.275***	−0.200
	(0.234)	(0.555)	(0.059)	(0.139)
Diff in Diff	0.184	−2.499**	0.931***	−4.295***
	(0.540)	(1.070)	(0.254)	(0.495)
Observations	8,686	1,867	92,082	24,866
R^2	0.001	0.004	0.003	0.001

Table 2.4: Temporal DID (East 2017 Closure) Longitude Relative to HNL: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	1.579***	0.738	4.537***	2.938***
	(0.287)	(0.484)	(0.145)	(0.326)
Closure Month−Day	0.712***	−0.435	0.955***	0.616***
	(0.112)	(0.313)	(0.035)	(0.077)
Diff in Diff	−1.800***	−3.947***	−1.183***	−4.933***
	(0.333)	(0.539)	(0.168)	(0.349)
Observations	15,561	4,124	156,420	38,559
R^2	0.004	0.042	0.029	0.007

Table 2.5: Temporal DID (East 2017 Closure) Catch: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	−1.717***	−1.492***	0.551***	−0.543**
	(0.285)	(0.481)	(0.139)	(0.265)
Closure Month−Day	0.121	−0.101	0.132***	0.031
	(0.168)	(0.403)	(0.043)	(0.103)
Diff in Diff	1.324***	1.308**	1.092***	1.683***
	(0.368)	(0.617)	(0.172)	(0.373)
Observations	15,561	4,124	156,420	38,559
R^2	0.002	0.002	0.003	0.001

Previously, treatment and control group were defined across years for one specific subgroup. Unlike the Temporal DID model, the Within-Year DID specification defines treatment and control group across the entire fishery, refer to Equation (2.2). The treatment groups vary between closure types and are defined as followed: all single permitted vessels for a western closure and all large vessels (>24 meters) for an eastern closure. Time horizons are still taken 30 days prior to closure start and 30 days post of closure end. DID coefficients estimate the effects of fishing within a treated group during a closure.

Tables (2.6) and (2.7) report the Within-Year DID results for the western 2016 and eastern 2017 closures respectively. During the western closure, single permitted vessels are displaced more east but there is still a positive statistically significant coefficient on catch. During the 2017 IATTC closure, large vessels remained west and reported a weakly positive effect on catch. The lack of statistical significance on the eastern estimates indicates the DID coefficient is not statistically different than zero.

Table 2.6: Within-Year DID (West 2016 Closure): The treatment group is defined as single permitted vessels. The control group is defined as dual permitted vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Days	1.857***	−0.834*
	(0.362)	(0.442)
Treatment Group	3.487***	0.131
	(0.305)	(0.380)
Diff in Diff	6.459***	1.268**
	(0.388)	(0.499)
Observations	9,803	9,803
R^2	0.281	0.001

Table 2.7: Within-Year DID (East 2017 Closure): The treatment group is defined as larger than 24m vessels. The control group is defined as less than 24m vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Days	−0.337**	1.256***
	(0.149)	(0.150)
Treatment Group	−0.514*	0.073
	(0.285)	(0.240)
Diff in Diff	−3.958***	0.305
	(0.309)	(0.321)
Observations	17,998	17,998
R^2	0.039	0.005

We further calibrate our model to exploit all sources of variation. Variations across fishery subgroups, across month-day combinations, and across years are leveraged in our

Triple DID model given by Equation (2.3). Tables (2.8) and (2.9) present results for the western 2016 and eastern 2017 closures respectively. Results are consistent with previous estimations. Longitude values for set locations are displaced more west while catch remains higher relative to non-closure years and control groups. There is a slight positive treatment effect on catch for an eastern closure, but these results are not significantly different from zero.

Table 2.8: Triple DID (West 2016 Closure): The treatment group is defined as single permitted vessels. The control group is defined as dual permitted vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Year	1.359***	−0.488
	(0.287)	(0.355)
Closure Days	3.905***	−0.493***
	(0.115)	(0.172)
Treatment Group	−1.318***	−1.112***
	(0.040)	(0.049)
Triple Diff in Diff	6.421***	1.269**
	(0.406)	(0.529)
Observations	460,531	460,531
R^2	0.069	0.002

Table 2.9: Triple DID (East 2017 Closure): The treatment group is defined as larger than 24m vessels. The control group is defined as less than 24m vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Year	4.761***	0.592***
	(0.129)	(0.122)
Closure Days	1.541***	0.418***
	(0.024)	(0.030)
Treatment Group	0.372***	0.697***
	(0.035)	(0.041)
Triple Diff in Diff	−3.797***	0.278
	(0.315)	(0.329)
Observations	442,047	442,047
R^2	0.021	0.003

2.5.2 Effective Closure

For the 2016 western and 2017 eastern closures, we find evidence consistent with the pollution haven hypothesis. Treated vessels are being displaced by the regulations but catch does not decrease relative to non-closure years and across treatment and control groups. It is worth noting that when an effective closure (both east and west) occurs, overall catch can sometimes be reduced. We now present the results for the 2015 effective closure. Additionally, a conclusive analysis for all closure types, in all closure years, is provided in the Appendix.

2015 marked the first year in which both sides of the Pacific experienced a closure simultaneously. Figure (2.7) presents comparisons for the 2015 effective closure. Due to restrictions in both the western and Eastern Pacific, the Sngl/>24 group will be most affected and the Dual/<24 group should be least affected. Comparing fishing conditions for the Sngl/>24 group (treated group) and the Dual/<24 (control group) would be the cleanest approach at visualizing changes in behavior post-closure. Unfortunately, the Dual/<24 group does not have enough data to visualize that comparison. Instead, we compare activity between the Sngl/>24 group and all other vessels during the 2015 effective closure. The top panel of the graph depicts relative longitude values, and the bottom panel displays catch. Activity for all vessels excluding the Sngl/>24 group appears to have a slight behavioral response to the 2015 effective closure. Vessels tend to stay more west during the closure and catch remains relatively constant at its pre-closure level. The Sngl/>24 vessels appear to have an even stronger response. Vessels appears to exit the fishery completely for the duration of the effective closure.

The temporal results for longitude and catch are summarized in Tables (2.10) and (2.11) respectively. All dual permitted groups might travel a bit more west, as shown by the positive coefficient on longitude, but these results are not statistically significant and cannot be differentiated from zero. Sngl/<24 vessels show a statistically significant location response and appear to set their hooks more east once the effective closure is in effect. Sngl/>24 vessels exhibit a significant western response, but this could also be caused by vessels returning to port and temporarily exiting the fishery.

Table (2.11) summarizes catch during the 2015 effective closure. A negative effect is

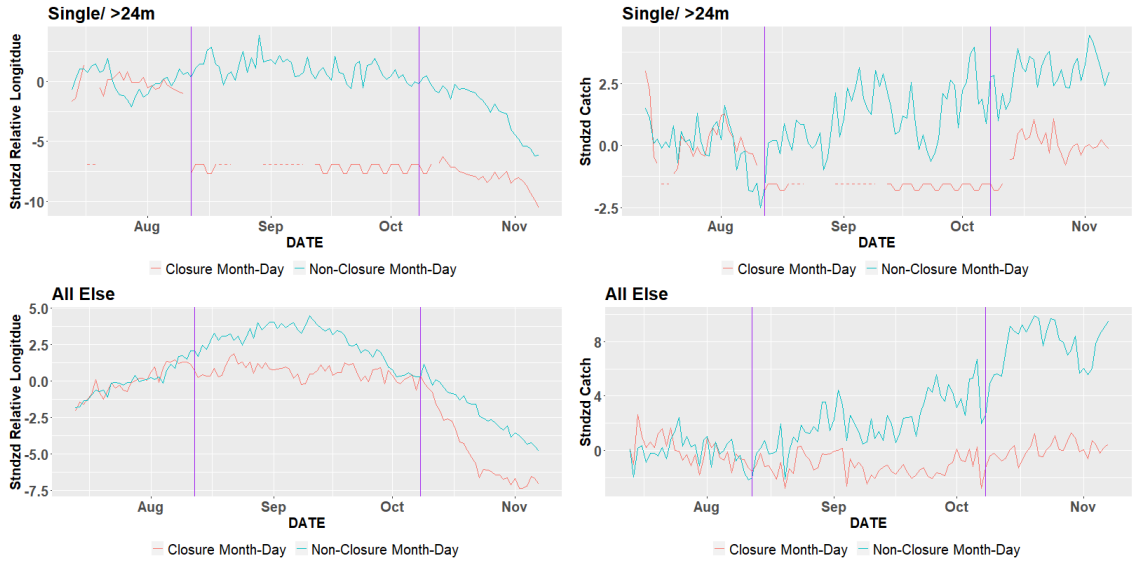

Figure 2.7: Comparing Fishing Conditions For the 2015 Effective Closure: All time series include fishing activities 30 days pre and 30 days post closure start and end respectively. Left panel represents longitude relative to HNL port and the right panel represents catch. During an effective closure, treated groups are single permitted vessels, larger than 24m in length and control groups are all other vessels.

estimated across all subgroups except the Dual/<24. Both single permitted groups have a statistically significant decrease in their catch indicating a disproportionate disadvantage to single permitted vessels.

We apply our Within-Year DID model to estimate the effects of the 2015 effective closure on the larger, single permitted vessels, refer to Table (2.12). During this period, the Sngl/>24 vessels show catch decreases significantly. Table (2.13) summarizes the Triple DID estimates for the effective closure. Results remain consistent. The treated group shows a statistically significant drop in catch relative to all other fishery subgroups.

Table 2.10: Temporal DID (Effective 2015 Closure) Longitude Relative to HNL: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	0.978***	−2.503***	4.934***	3.555***
	(0.343)	(0.472)	(0.123)	(0.246)
Closure Month−Day	1.634***	0.496	1.321***	1.896***
	(0.138)	(0.330)	(0.042)	(0.083)
Diff in Diff	0.069	−1.833***	5.416***	−11.177***
	(0.540)	(0.566)	(0.148)	(0.445)
Observations	10,311	2,652	107,501	28,278
R^2	0.017	0.050	0.098	0.026

Table 2.11: Temporal DID (Effective 2015 Closure) Catch: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	1.636***	1.602**	2.253***	2.100***
	(0.424)	(0.673)	(0.164)	(0.343)
Closure Month−Day	0.094	−0.330	−0.202***	0.169
	(0.202)	(0.453)	(0.053)	(0.122)
Diff in Diff	0.264	−0.494	−0.796***	−7.404***
	(0.671)	(0.912)	(0.240)	(0.355)
Observations	10,311	2,652	107,501	28,278
R^2	0.003	0.004	0.004	0.002

Table 2.12: Within-Year DID (Effective 2015 Closure): The treatment group is defined as single permitted, larger than 24m vessels. The control group is defined as all other vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Days	5.421***	−0.822***
	(0.150)	(0.211)
Treatment Group	−0.808***	0.412
	(0.265)	(0.364)
Diff in Diff	−17.515***	−6.434***
	(0.422)	(0.396)
Observations	10,525	10,525
R^2	0.134	0.004

Table 2.13: Triple DID (Effective 2015 Closure): The treatment group is defined as single permitted, larger than 24m vessels. The control group is defined as all other vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Year	6.887***	2.098***
	(0.112)	(0.145)
Closure Days	4.108***	−0.333***
	(0.033)	(0.040)
Treatment Group	−0.422***	0.420***
	(0.029)	(0.036)
Triple Diff in Diff	−18.231***	−6.905***
	(0.429)	(0.409)
Observations	465,529	465,529
R^2	0.078	0.002

2.6 Discussion

This study tests for the presence of a pollution haven in a high seas longline fishery. We first segregate each closure to represent one policy event, a western closure, an eastern closure, or an effective closure. When defining both the western and eastern closures independently, results from our difference in difference estimation consistently find a displacement of effort among the treated groups or, in extreme events, subgroups are forced to stop fishing completely. Despite a closure being in effect, the treated groups typically observe an increase in catch relative to non-closure years (Temporal DID) and relative to control groups (Within-Yr and Triple DID). Effective closures (both west and east closed) appear to have more successful outcomes: catch decreases during closure years relative to non-closure years for most of the fishery subgroups (Temporal DID). In addition, when defining our treatment and control groups across the fishery (Within-Yr, Triple DID), catch consistently decreases among the treated group relative to the control group.

Despite the evidence that pollution havens occurred during the western 2016 and eastern 2017 closures, not all closures lead to a pollution havens style outcome. Some closures are more successful than others in reducing total catch, specifically the early eastern closures. During the first three eastern closures (2013, 2014, and 2015) catch was reduced for all subgroups during the closure year relative to non-closure years, refer to Appendix Tables (B.5), (B.6), and (B.7). Other closures, such as the effective closures that occurred during 2015, 2016, and 2017, appear to have a dramatic effect on the most impacted vessels, causing single permitted, large vessels to temporarily exit the fishery. However, most vessels are unaffected and seem to catch even more during closures. Specifically, dual permitted vessels that measure less than 24 meters in length consistently have higher catch rates during western closures relative to the same month-day combinations in all other non-closure years. During the more recent eastern closures (2016 and 2017), smaller single permitted vessels appear to be favored by the policy intervention, also experiencing higher catch rates during closure years. During all three effective closures, some form of the smaller vessel groups (either Dual/<24 or Sngl/<24) seem to have benefited more during the closure years relative to non-closure years as shown by an increase in fishing productivity (e.g., higher catch rates).

The findings of this study bring to light two main issues. First, these results provide evidence in support of the pollution haven hypothesis within the longline fishing industry. Effort is displaced at higher cost to the fishers but without reducing catch. Second, the analysis, specifically our Temporal DID model, brings attention to the inequality of the regulations. Policy beneficiaries that can still maintain operations during the closures observe higher catch rates within closure years relative to catch by the same vessel in all other non-closure years. The increase in catch rates could possibly be explained by the lack of competition during a closure. Measuring the full extent of the inequality caused by the regulations is beyond the scope of this study but can act as the basis for future work.

Chapter 3

Estimating the Inverse Price Elasticity of Demand for Pacific Bigeye Tuna

3.1 Introduction

The longline fishery in the Pacific is highly regulated due to threats of species over exploitation. Bigeye tuna has a high commercial value and is the main target of this fishery. As a means to mitigate overharvest, annual fleet quotas are enforced. Assuming all agents act rationally, current policies have been criticized to wrongfully incentivize fishermen by cultivating a 'race to fish' behavior before the fleet quota is reached. In theory, this can lead to periods of flooding market supply, causing a devaluation of bigeye tuna.

Under certain market conditions, incentivizing cooperation amongst fishermen can offer higher payoffs than policy schemes that cultivate competition. As an alternative to a top-down management approach, fisheries that have a combination of effort coordination and revenue pooling outperform fisheries regulated by other forms of hierarchical management Uchida (2010). If demand is inflexible to a change in prices, fisherman could unanimously reduce market supply and potentially receive a price that is more reflective of the true value.

The price elasticity of demand (PED) is used as a metric to gauge whether market supply is at its profit maximizing level, or, if profits can be further increased by supply

manipulation. As outlined in Sun et al. (2019), if price increases more rapidly than supply falls, then restricting supply would increase total revenue. The proposed study utilizes a detailed data set on bigeye tuna transactions to obtain an unbiased estimate of the inverse price elasticity of demand in the Honolulu fish auction. Our study leverages three category 4 hurricanes that simultaneously entered the Pacific in 2015 as a means to isolate shocks in supply which, we argue, are orthogonal to demand.

Although we are not the first to apply an instrumental variables (IV) framework to estimate the PED of a fishery, identifying a truly exogenous shift in supply is rare (Angrist et al., 2000; Tokunaga, 2018). The novelty of this study lies in our identification strategy. We argue that certain extreme weather events have a direct impact on fisherman behavior without altering demand. To prove demand was not affected by the 2015 hurricanes, we utilize airline data that documents daily passenger arrival count. The conjecture is that if visitors are still willing to visit the island chain during the storms, buyers will not be deterred from attending the auction.

Our ordinary least squares (OLS) estimation finds that demand is elastic, which is consistent with previous elasticity estimations (Angrist et al., 2000; Tokunaga, 2018; McConnell and Strand, 2000). Despite the congruency, our IV model consistently measures elasticity to be more inelastic then OLS. In the context of current fishery conditions, if cooperation amongst fishermen can be incentivized and landings could be coordinated, higher profits could potentially be reached relative to the current market environment. In addition, these results highlight the importance of correcting for potential endogeneity and measuring an unbiased estimate of elasticity of demand.

3.2 Background

3.2.1 The Market

The Honolulu Auction was established on August 5, 1952 by the United Fishing Agency and has provided a platform in which wholesale buyers and sellers can negotiate trade. Rarely will you find a household consumer assessing each fish displayed on the auction floor. Instead the wholesalers are bidding veterans that diligently show up at 4:45 am, 6 days a

week, ready to compete for the day's landings. Whether they are buying for a downtown grocery store in Honolulu or an upscale restaurant in Manhattan, each wholesaler typically represents a host of buyers. Occasionally a wholesaler and a captain will agree on a private trade, but more often, the majority of fish that are landed at the Honolulu port end up on the auction floor. Each morning, the auction opens by displaying a list of the estimated market volume of each species caught by each vessel. For the larger species, the auctioneer will proceed down the rows of pallets, auctioning off each individual fish displayed.

Figure 3.1 summarizes average annual measurements of pounds landed, pounds sold, number of permit holders, number of trips taken, price per pound, and total revenue. All values are standardized where the y-axis represents percentage deviations from the baseline year of 2004. Over a 14-year period, landings, market volume, price per pound, and revenue have all experienced an increasing trend, yet the number of permit holders and trips taken have remained relatively constant.

3.2.2 Previous Work

The relationship between prices and effort has been documented within the fisheries literature. Reductions in harvest can be off-set by a reduction in operational costs due to an increase in stock abundance and a decrease in effort Kompas et al. (2006); Bertignac et al. (2000). By defining a Generalized Synthetic Inverse Demand System (GSIDS), Sun et al. (2017) shows revenue can be sustained by reducing global supply of all tuna species. This sustainability is ensured by prices proportionally rising relative to the reduction in supply. Chiang et al. (2001) also utilizes an inverse demand framework and finds a 1% increase in inventory of frozen bigeye and yellowfin tuna would result in a 0.07% and 0.012% cent decline in prices respectively.

The use of hedonic models to identify influential drivers of market conditions has a wide application in the resource economics literature. There are a few studies that have applied hedonic models to the bigeye tuna market in Hawaii (McConnell and Strand, 2000; Carroll et al., 2001). McConnell and Strand (2000) identifies three main drivers of price for tuna in the Hawaii market: species and handling methods, quality, and daily supply. Out of the

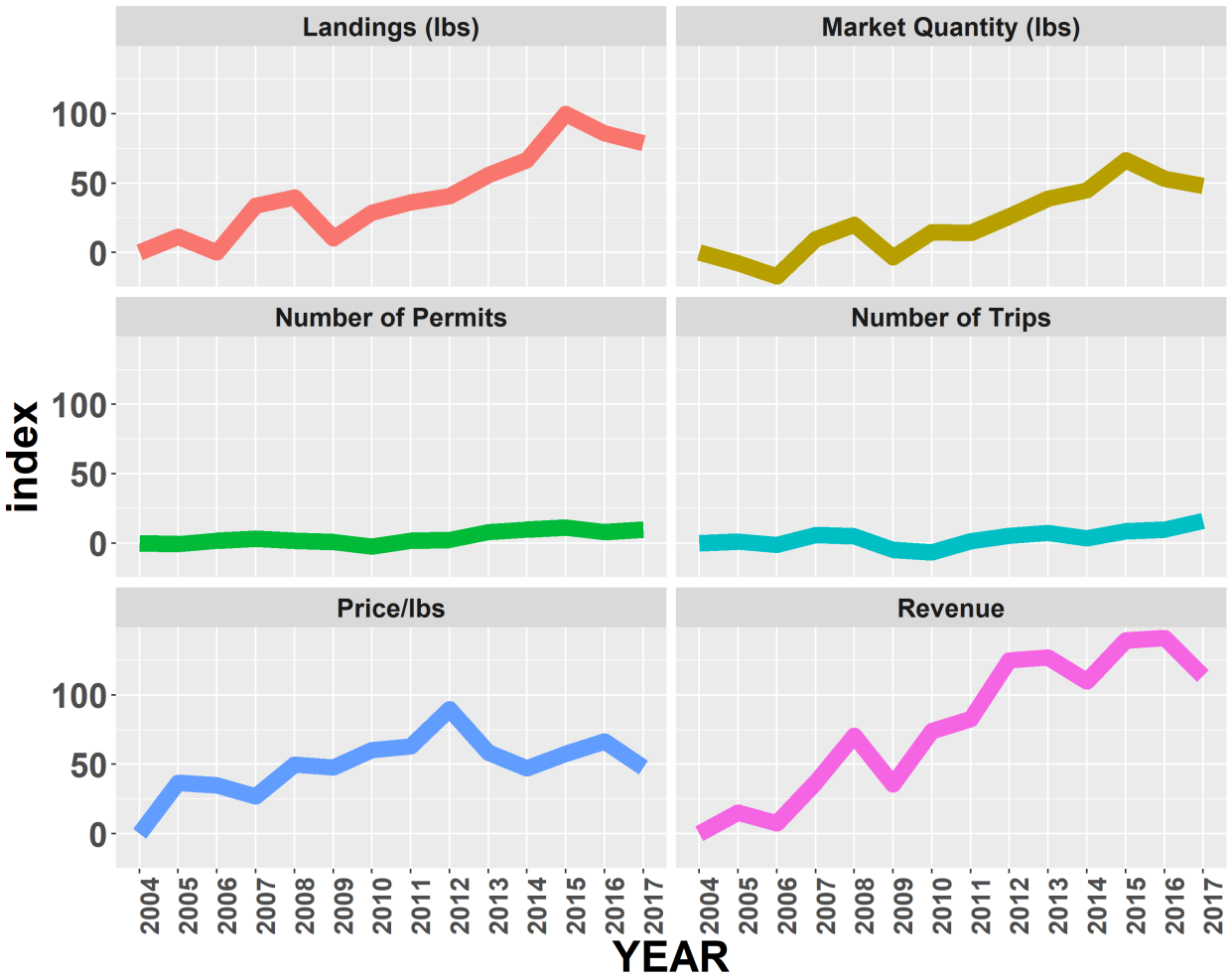

Figure 3.1: Market Conditions Over Time: Annual average pounds landed, pounds sold, number of permit holders, number of trips taken, price per pound, and revenue are displayed. To unify variable scale, all trends are standardized by subtracting the mean and dividing by the standard deviation.

three tuna species analyzed, bigeye was found to be the most responsive to fluctuations in landings. By running a simple OLS model, the authors find that a 1% increase in bigeye will lead to a 0.074% decrease in price, suggesting demand is elastic.

In addition to quality and quantity, seasonality plays an important role in tuna pricing. Pan and Pooley (2004) explores how seasonality affects tuna prices both directly and indirectly. An increase in demand during the holidays can result in a temporal fluctuation in price, but price can also be indirectly driven by temporal changes in fish quality. Estimating price as a function of seasonally changing covariates using an ordinary least squares model, the authors find intra-annual variation in quality, quantity, and demand have a significant influence on price. The authors did not log-transform the model so coefficients cannot be interpreted as elasticities. Nonetheless, they found a -0.0038 reduction in price for every

additional 1,000 pounds landed.

The use of hedonic and OLS models estimates correlation between price and quantity but correlation does not infer causality. Angrist et al. (2000) was one of the first papers to utilize environmental conditions as an instrument to estimate the price elasticity of demand for whiting in New York. By using a two stage least squares model they instrument for prices using a set of dummy variables or weather indicators that capture weather conditions near the coast. They estimate the price elasticity of demand to be -0.947 indicating demand for whiting is slightly inelastic. Unlike Fulton, Hawaii does not follow a posted offer market, all fish landed are bought on the same day. During each period, quantity demanded will equal quantity supplied because prices will adjust until markets clear. Following Angrist et al., Tokunaga (2018) utilizes a two stage least squares model to estimate the price elasticity of demand for Bluefin Tuna in Tokyo, Japan. Instrumenting for price using quantity supplied, Tokunaga estimates elasticity to be -1.267, indicating an elastic demand for bluefin tuna. Like Honolulu, Tsujiki Fish Market is an auction, port landings, price, and auction volume are naturally highly correlated. In order for an instrument to be valid, it must hold that landings only affect demand through its influence on supply. Naturally, there could exist some exogenous force that is influencing landings and demand that can result in a biased estimate.

Table 3.2 provides a summary of previous estimates of the price elasticity of demand.

Table 3.1: Previous Price Elasticity of Demand Estimates

Paper	**Inverse PED**	**PED**	**Elastic/ Inelastic**
McConnell & Strand 1998	-0.074	-	Elastic
Tokunaga 2018	-	-1.267	Elastic
Angrist 2000	-	-0.947	Inelastic

The aim of the proposed study is to obtain an unbiased estimate of the inverse price elasticity of demand. Like Angrist et al. and Tokunaga, we leverage exogenous shocks to supply by defining an instrumental variable that represents extreme weather events. The vast, open waters of the Pacific is a breeding ground for hurricanes in the summer months. As they move through the Pacific, these storms can impact the productivity of a fishing trip. Using three storms that affect supply but appear to have no effect on demand, we are able

to obtain an unbiased estimate of the inverse price elasticity of demand for bigeye tuna in Hawaii.

3.3 Data

We utilize federally issued data sets provided by the National Marine Fishery Service (NMFS) that detail catch and species interaction. The National Oceanic Atmospheric Administration requires all captains to comply with documentation standards at the trip level by recording catch composition by species for each set. We aggregate the number of bigeye tuna kept across fishing trip and use the *Return to Port* date to quantify daily landings. As a result, we obtain total landings in pounds at the daily level.

Hawaii Integrated Dealer Data document price and market volume and is provided by the Hawaii Division of Aquatic Resources. We merge both data sets by date of transaction and date of landings to produce a repeated cross sectional data set. Data statistics can be found in Table (3.2).

The inverse PED is estimated by measuring the price response to an exogenous shift in supply that is being driven by environmental conditions. Because the three category 4 storms entered the Pacific in 2015, it is intuitive to compare the price response to landings during the hurricane days to all other prices in 2015.[1]. There were 195,679 big eye tuna transactions in 2015. Of these transactions, 5,391 took place during a hurricane day[2].

Table 3.2: Data Statistics

Variable	**Minimum**	**Maximum**	**Mean**
Date	Jan 05, 2015	Dec 31, 2015	-
Price ($/LBS)	$0.10	$16.5	$3.97
Landings (10,000 LBS)	0	148.82	42.81

[1]In 2015 the deep set fishery experienced a closure. The hurricane duration was completely encompassed in the closure time period, but, as a robustness check we control for closure days. In addition, we also ensure our findings do not suffer from sampling bias by expanding our sample period to represent one year prior and one-year post 2015. All robustness checks can be found in the Appendix Section.

[2]A hurricane day is defined as having at least one of three named storms in the Pacific

3.4 Identification Strategy

3.4.1 Instruments Defined

The Pacific Ocean surrounding the Hawaiian Islands can experience some of the strongest hurricanes annually. Each summer, the central Pacific enters the hurricane season beginning on June 1st. Luckily, these storms rarely make landfall, and, at most, the island might suffer minimal damages due to heavy rain or flooding. Fishing vessels, on the other hand, are more exposed to the track of the storms and must remain vigilant with each announced hurricane.

During summer months, the historical fishing grounds are north east of the Hawaiian Islands, moving farther away from the coast due to warm summer waters. 2015 was a record-breaking year for annual hurricanes with 26 named storms entering the Pacific, seven of which posed a threat to the island chain. But it was the three category 4 hurricanes, Kilo, Ignacio, and Jimena, that made history by simultaneously entering the northern part of the Pacific Ocean. A timeline of the hurricanes is given in Table 3.3.

The market response to an extreme weather event can range depending on the storm's path, environmental severity, and fishing behavior. If the storm is passing through the Pacific in a different location than fishing activity, there may be little to no effect. If the storm intersects the historical fishing area, fishermen may decide to race back to port or to stay out at sea in hopes to avoid the storm. In either case, this may lead to a jump or dip in market supply.

Table 3.3: 2015 Hurricane Timeline

Storm	Start	End
Kilo	August 22, 2015	September 1, 2015
Ignacio	August 25, 2015	September 4, 2015
Jimena	August 26, 2015	September 1, 2015

To see how fisherman react to the three category 4 hurricanes, we plotted a time series of daily landings and daily average price (refer to Figure 3.4). The vertical lines show the time duration in which there was at least one of the three storms present in the Pacific.

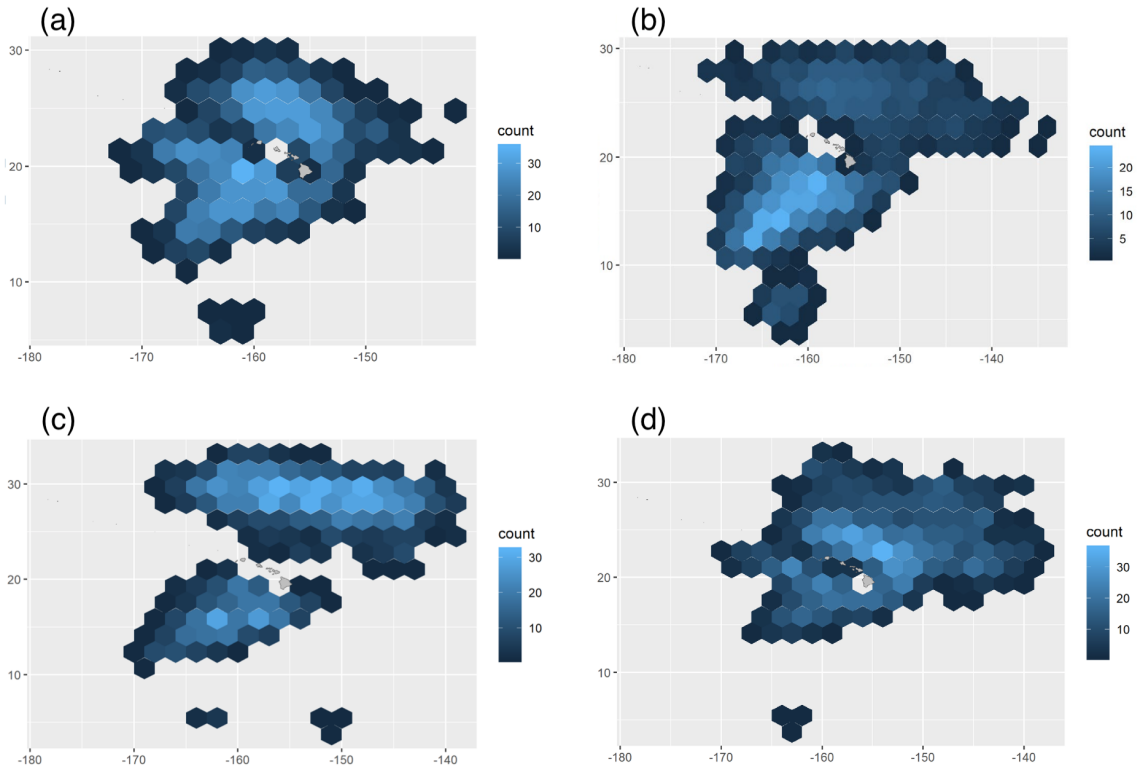

Figure 3.2: Seasonal Fleet Dynamics: Historical fishing grounds by season for the deep set fishing fleet. Panel (a), (b), (c), and (d) represent winter, spring, summer, and fall respectively. Color gradient represents the spatial density of fishing distribution.

To unify the scale of measure between the variables, the data is standardized such that each observation is found by subtracting the pre-hurricane mean and dividing by the pre-hurricane standard deviation. For each day t, we calculate the daily aggregate landings or the daily average price, subtract the mean value taken across all pre-hurricane days, μ, and divide by the pre-hurricane standard deviation, σ. For example, a zero value on day t indicates the daily statistic equals the average before the hurricane hit. Specifically, $\sum_i LANDINGS_{i,t} = \mu_{landings}$ and $\overline{PRICE}_t = \mu_{price}$. Expressing the time series in this form allows us to interpret the values as deviations away from the pre-hurricane mean. Equations (3.1) and (3.2) represent the standardization for landings and price respectively.

$$standardized\_LANDINGS_t = \frac{\sum_i LANDINGS_{i,t} - \mu_{landings}}{\sigma_{landings}} \tag{3.1}$$

$$standardized\_PRICE_t = \frac{\overline{PRICE}_t - \mu_{price}}{\sigma_{price}} \tag{3.2}$$

During the initial days of the hurricane, we observe a negligible effect on landings for

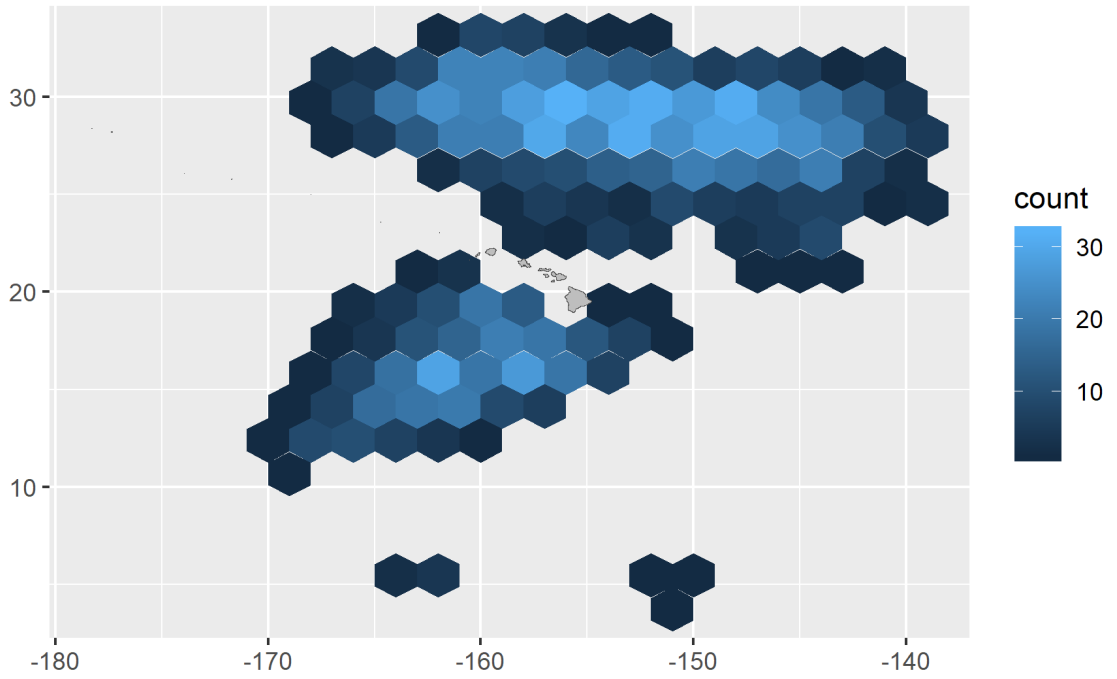

Figure 3.3: Summer 2015 Fleet Dynamics: Fishing grounds during the 2015 summer season. Color gradient represents the spatial density of fishing distribution.

hurricane Kilo. Both hurricane Ignacio and Jemina show a slight increase in landings in the initial hurricane days. As the hurricanes progresses, landings dips slightly for all three hurricanes, and the price for bigeye increases dramatically.

Coincidentally, these three hurricanes coincided with policy restrictions that could have confounding effects which would lead to an overstated price response. These policy changes take the form of catch quotas. During 2015 the longline fishery experienced a fishery closure which resulted in a portion of the fleet to cease all fishing activity. As we proceed with our analysis, we control for these policy changes and present the results in Section 3.5.2. Additional closure specifications can be found in the Appendix.

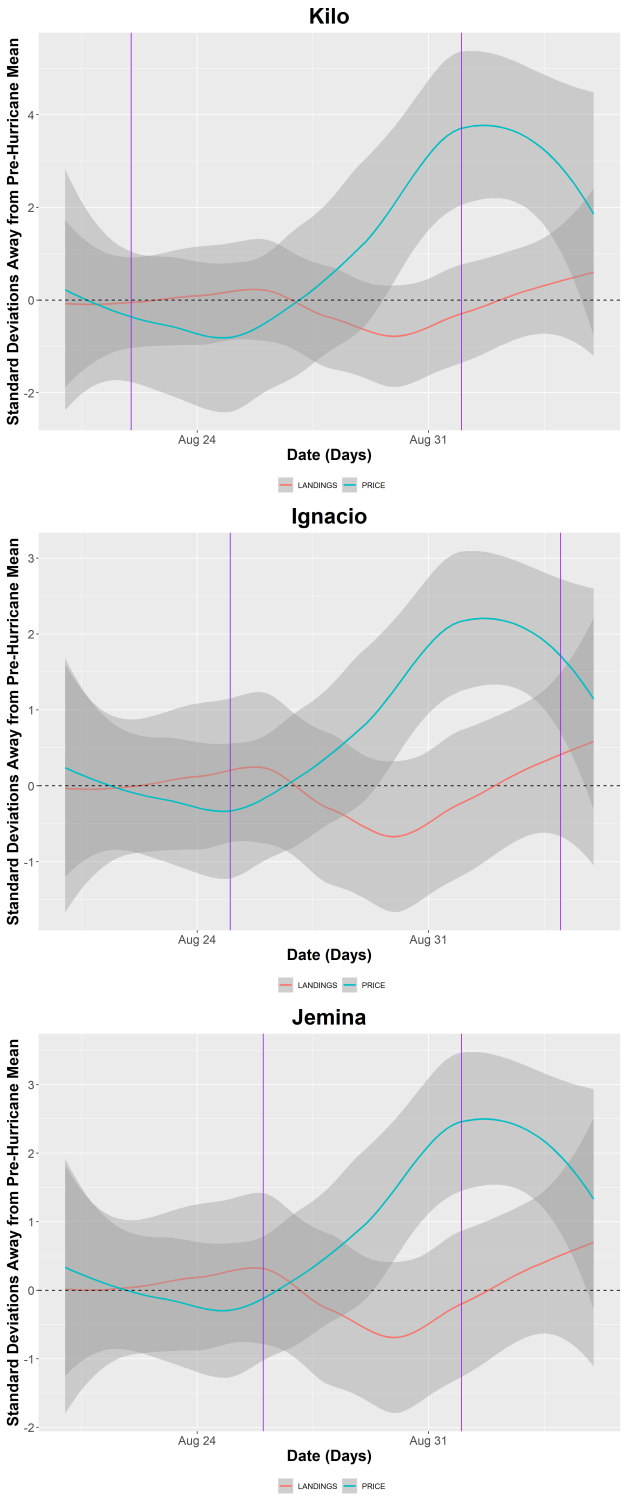

Figure 3.4: Hurricane Days Price and Landings: Each panel depicts the time trend of standardized landings and standardized price for each individual hurricane. The vertical purple lines indicate hurricane start and end. Standardizations are based off of the pre-hurricane mean and standard deviation. Plots extend from August 20, 2015 to September 5, 2015.

3.4.2 Exploring Identifying Assumptions

Angrist et al., 2000 outlines the four main assumptions needed to measure consistent estimates of an instrumental variables model. The first assumption, Independence, implies there is no confounding effect, meaning, there does not exist an exogenous factor that will affect the instrument and the outcome variable simultaneously. An example of a violation would be wind speed increasing the chances of a hurricane and simultaneously increasing demand. The second assumption is the 'Non-Zero effect of Instruments on Prices', which states that average prices will change as the instrument value varies. The second assumption assures that the instrument does, in fact, have an effect on the variable of interest. The third assumption introduced is the idea of monotonicity. Monotonicity suggests that the direction of the relationship between the instrument and the endogenous variable is well defined. In other words, if an increase in the instrument value leads to an increase in price, then a decrease in the instrument should not observe an increase in price.

The final assumption in an IV model is the exclusion restriction which states that the instrument's effect on quantity is only channeled through supply. If the presence of a hurricane changed consumers' propensity to buy bigeye, our identification strategy would fail, and our estimates would be biased. Historically, there are many natural disasters that would challenge our assumption. When tropical storms threaten to make landfall, schools and businesses close as the public races to buy necessities and non-perishable goods. In these circumstances, the extreme weather event would invalidate our identification strategy by imposing a supply effect *and* demand effect.

In this section we argue that the proposed 2015 hurricanes influence fisherman behavior yet have no effect on demand. To explore this assumption, ideally, we would want to see if there was a dip in auction attendees during the hurricane days relative to non-hurricane days. Unfortunately, we do not have auction records thus we cannot make these observations. Instead, to illustrate our conjecture, we utilize airline passenger arrival count provided by the Hawaii Department of Business, Economic Development, and Tourism. This data set records the number of daily occupied airline seats for flights entering the state of Hawaii. Our hypothesis is, if a hurricane threatens to make landfall the public will react by canceling their trip or the airlines will react by flight cancellations. In either case, a sudden change

in flight behavior that appears to be correlated with the presence of a hurricane is used as a proxy to gauge whether or not an auction buyer is hesitant to buy during the time of a storm.

To see if our hypothesis holds, we first investigate how people respond to a threatening hurricane by considering Hurricane Lane in 2018. Lane was the second category 5 hurricane to travel within 350 miles to the island chain causing federal buildings, state buildings, and schools to close. Though the storm did not make landfall, it brought the second highest rainfall total, causing massive flooding to the windward side of most islands. The Federal Emergency Management Agency provided the state $2.5 million in disaster relief aid yet the total damages were estimated to be about $42.5 million dollars.

Hurricane Lane formed on August 15, 2018 and dissipated on August 29, 2018. All islands were under a hurricane advisory between August 22nd to the 26th where the hurricane hit peak intensity on the 22nd. In addition to schools and business closing, we utilize our airlines data set to see if visitors were more hesitant to visit the islands during the storm [3]. The red line in Figure 3.5 represents airline seat occupancy count during each day of Hurricane Lane. The box plots represent the distribution of visitor arrivals in the same month-day but for all other years. We standardized the data to correct for the natural upward time series trend by subtracting the yearly mean and the yearly standard deviation. From Figure 3.5 we see passenger arrivals were below average between August 22nd and August 24th which was likely caused by flight cancellations and a hesitation to visit the islands during the hurricane's peak intensity. An extreme weather event like Hurricane Lane would be an example of an instrument that would fail to satisfy the exclusion restriction, as it likely affected demand for fresh fish.

[3] http://files.hawaii.gov/dbedt/economic/data_reports/special/daily-pax-update.xls

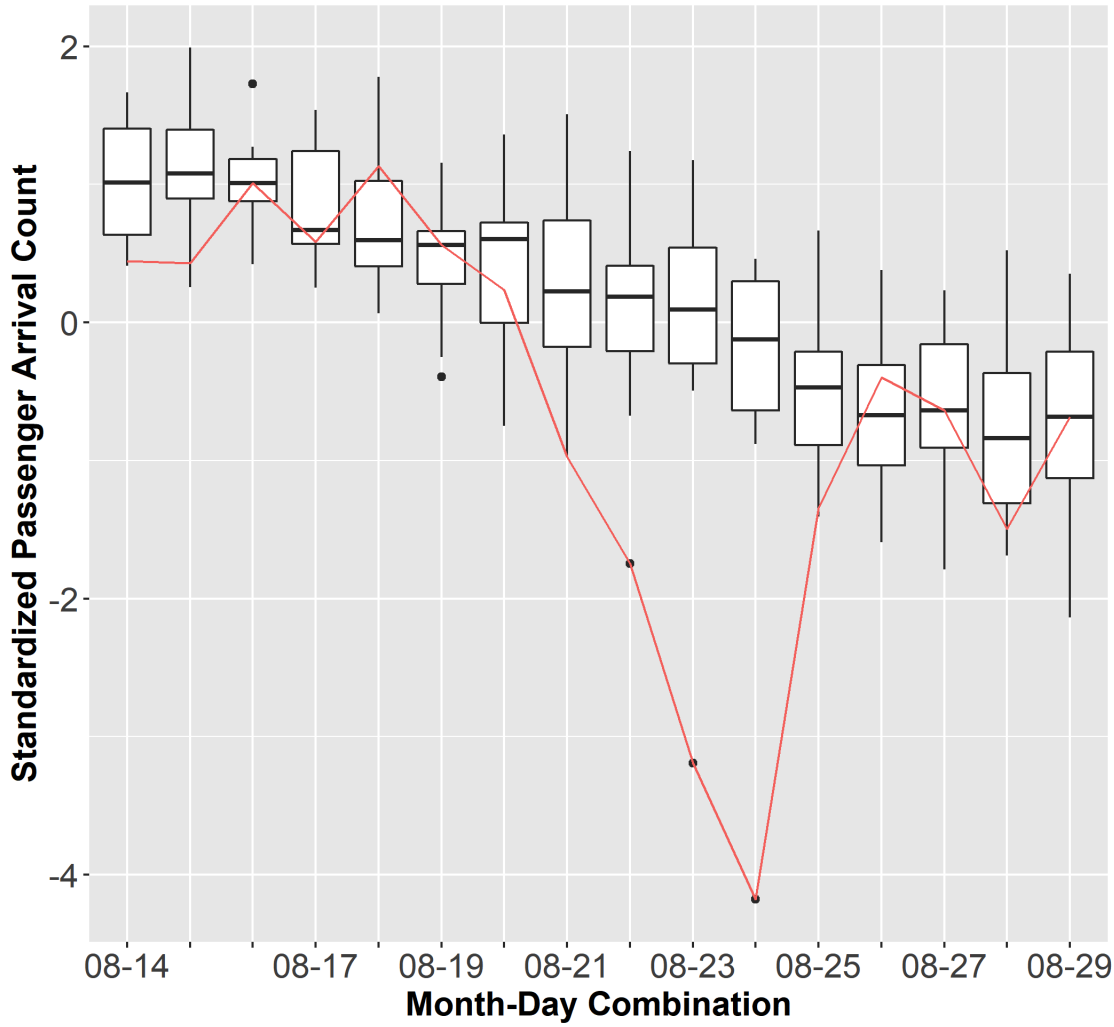

Figure 3.5: Airline Arrivals (Hurricane Lane): Comparing passenger arrival count between hurricane days to the distribution of arrival count in all other non-hurricane days. Box plots depict the distribution of passenger arrivals on each month-day of the hurricane days for all non-hurricane years. The solid line represents the observed passenger arrival count during each hurricane day, within the hurricane year. There is a below average drop in passenger arrivals during August 22nd and August 24th.

Applying the same methodology to the 2015 storms, we explore the exclusion restriction for Ignacio, Jimena, and Kilo. We define our hurricane days as any day that experienced at least one of the three storms and, as we previously done, we compare these arrival counts to the passenger arrival counts during the same month-day, in all other years. From Figure 3.6 we see that the number of visitor arrivals did not drop during the hurricane days relative to the average airline seat occupancy for all other years. We presume that if the hurricanes did not deter visitors from the islands, the hurricanes were not likely to deter wholesalers from attending the auction.

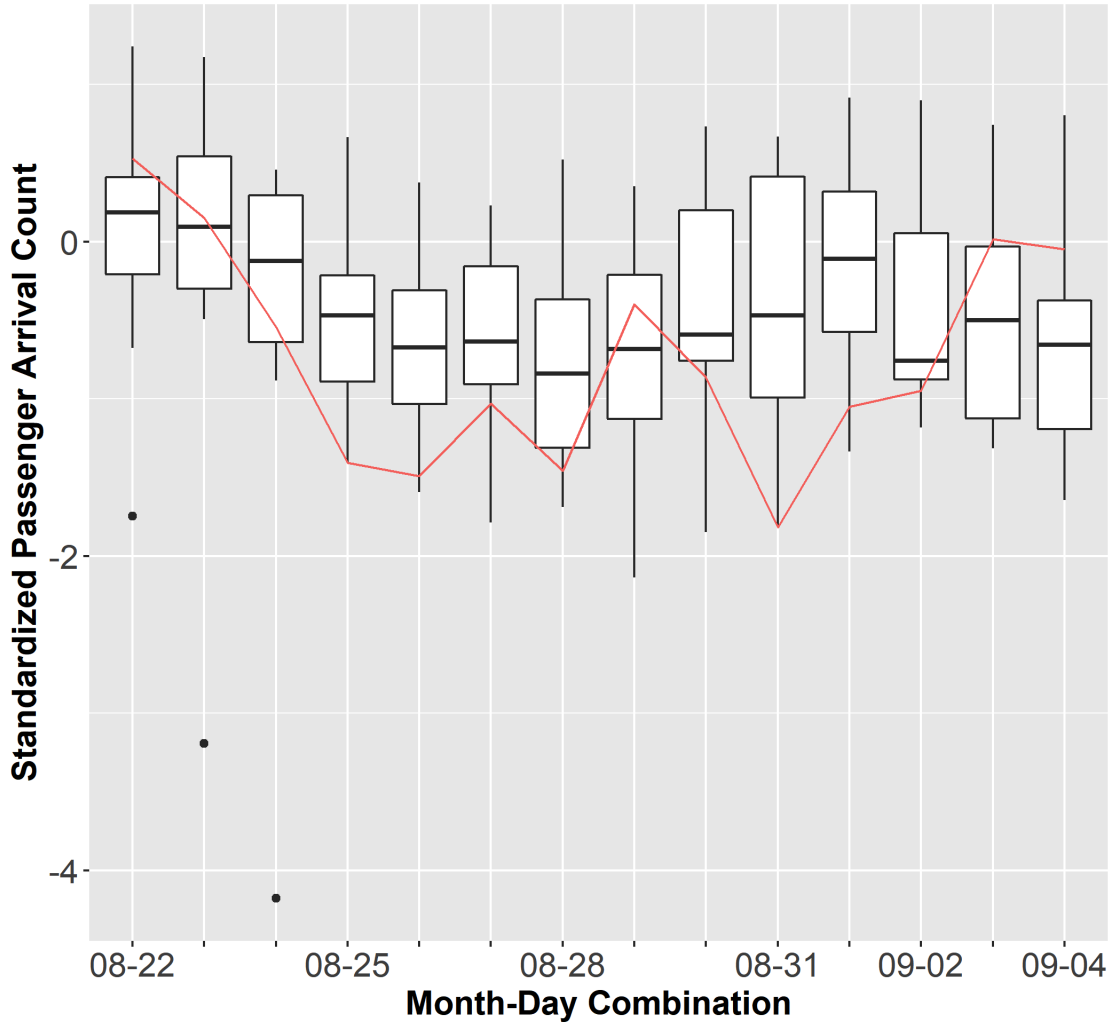

Figure 3.6: Airline Arrivals (2015 Hurricanes): Comparing passenger arrival count between hurricane days to the distribution of arrival count in all other non-hurricane days. Box plots depict the distribution of passenger arrivals on each month-day of the hurricane days for all non-hurricane years. The solid line represents the observed passenger arrival count during each hurricane day, within the hurricane year. The aggregate daily passenger arrivals during 2015 hurricanes fluctuates around the distribution of passenger arrivals for the same month-day combination for all other non-hurricane years.

In addition to the quantitative evidence, we also explore the effects on demand qualitatively by first looking at three different reputable news outlets that covered the storm [4]. Scientists and reporters marvel at this historical event in which three category 4 storms simultaneously move through the northern Pacific yet, all sources report that these hurricanes posed little to no threat to the island chain. Quoting from the climatology news website

[4] https://www.accuweather.com/en/weather-blogs/stormblog/hurricanes-kilo-ignacio-and-jimena-make-history-in-pacific/52117672
https://www.washingtonpost.com/news/capital-weather-gang/wp/2015/08/31/for-the-first-time-on-record-3-major-hurricanes-spin-simultaneously-in-northeast-pacific/
https://www.climate.gov/news-features/event-tracker/central-pacific-hurricane-party-three%E2%80%99s-company

hosted by NOAA, "However, the best news about these three juggernauts is that they pose little threat to land as they churn away in the waters of the northeast Pacific Ocean." In addition, there was no documented evidence that schools or businesses were closed during the time of the hurricanes.

3.4.3 Specification

In a typical posted offer market quantity is a function of price. A seller will set the price and market quantity will be determined by a buyer's willingness to pay, thus estimating the price elasticity of demand would be found by regressing quantity demanded onto price. In the Hawaii market, the majority of bigeye tuna transactions take place in the Honolulu auction. Unlike a posted offer market, fishermen have no control over market prices, fish landed on day t will influence the prices observed on day t, but they must land their catch in the morning and accept any price offered. In this type of auction structure, price is a function of market quantity. Due to the market structure of the fishery, instead we estimate the *inverse* price elasticity of demand by defining our dependent variable as price and our potentially endogenous independent variable as quantity landed.

Quantity landed is a sufficient proxy for market quantity, or quantity demanded, due to the market clearing condition of the auction. The endogenous model we wish to estimate is given by Eq (3.3).

$$PRICE_{i,t} = \beta_0 + \beta_2 QUANTITY_t + \mathbf{MF} + \epsilon_{i,t} \tag{3.3}$$

Where $PRICE_{i,t}$ is the price per pound for the i^{th} bigeye tuna sold in time period t, $QUANTITY_t$, is the pounds of bigeye that enters the market on a given day, **MF** is month fixed effects, and $\epsilon_{i,t}$ is the random component. Our variable of interest, β_2, represents the inverse price elasticity of demand.

Naïvely regressing price onto market quantity would ultimately lead to a biased estimate of the inverse price elasticity of demand because it could be that there is some unobserved variable that is driving both prices and market quantity that our model is not accounting for. For example, if Hawaii receives a large number of imports on a given day, the demand of

the wholesaler will be less responsive to changes in the day's port landings. To address this endogeneity concern, we utilize an instrumental variable approach and define our instrument using the Category 4 hurricanes that occurred simultaneously in the summer of 2015.

Our instrumentals variable model is represented by equations 3.4 and 3.5 where **MF** is month fixed effects, and z_t is the instrumental variable. $\widehat{LANDINGS_t}$ is the fitted values from our first stage regression, thus β_1 is our coefficient of interest. All variables are log valued except for dummy variables. Coefficients can be interpreted as such; a one percent increase in *Landings* will lead to a β percentage change in *Price*, which is an inverse elasticity.

We run our model using three different identification strategies. In the simplest specification (BIV), we use a binary indicator variable that takes a value of one if the transaction took place during a hurricane day and zero otherwise. The BIV model treats each hurricane day the same, meaning, it does not control for the differences in fishermen response to the first hurricane day as opposed to the 10th hurricane day. As a means to account for response-dynamics, we separate the hurricane days into multiple indicator variables. In our second specification (3IV), we disaggregate our instrument into three different binary variables that represent Ignacio hurricane days, Jimena hurricane days, and Kilo hurricane days. As our third specification (14IV), we disaggregate our instrument further by running our model using 14 different binary indicator variables to represent the 14 days in which one of the three hurricanes were present in the Pacific (14IV).

Stage 1:

$$ln(LANDINGS)_t = \alpha_0 + \alpha_1 z_t + \mathbf{MF} + \epsilon_t \tag{3.4}$$

Stage 2:

$$ln(PRICE)_{i,t} = \beta_0 + \beta_1 \widehat{LANDINGS_t} + \mathbf{MF} + \epsilon_t \tag{3.5}$$

3.5 Results

3.5.1 BIV, 3IV, and 14IV Results

Table 3.4 represents the binary indicator variable (BIV) model. Month fixed effects were used as a means to control for month-to-month variation which is represented by Column (2). In both specifications, the BIV model shows a negative correlation between hurricane days and landings indicating that on average, one extra hurricane day would lead to a drop in landings. The second stage results of the BIV model are represented in Table 3.5 where Column (1) is the baseline ordinary least squares (OLS) model, Column (2) is the BIV model ran without month fixed effects, while Column (3) controls for month-to-month variation by including month fixed effects.

The OLS estimate of the inverse price elasticity of demand is -0.0134. Inverting the OLS coefficient we find that a 1% increase in price would lead to a 74% decrease in market demand, suggesting demand to be highly elastic. Once correcting for endogeneity by using an instrumentals variable approach, our BIV model estimates the inverse price elasticity of demand to range between -2.244 and -5.365. Inverting these findings, we interpret the results as a 1% increase in price causes market demand to decrease between a range of -0.186% and -0.446%. Contrary to the OLS estimate, the BIV model indicates that demand is inelastic.

Table 3.6 represents the first stage results of the 3IV Model. As hypothesized, we observe a spike in landings as the first hurricane enters the fishing grounds followed by a subsequent drop in quantity supplied as the other two hurricanes move through the Pacific. The magnitude of correlation between the instruments and landings decreases once monthly fixed effects are accounted for (Column 2), but the direction of the correlation remains the same across model specifications. Table 3.7 summarizes the second stage results. Column (1) represents the OLS model, Column (2) does not account for month-to-month variation, and Column (3) includes month fixed effects. Once month-to-month variation is controlled for, the size of the bias shrinks as compared to the OLS baseline, but both IV specifications consistently measure demand to be more inelastic than OLS.

We disaggregate our instruments further such that each hurricane day represents its own instrument. We summarize the first stage results in Table 3.8 and present the second stage

results in Table 3.9. First stage coefficients are consistent across various degrees of month fixed effects in which we find an initial jump in landings during the first couple hurricane days, and then a fall in the following days. Though the elasticity is estimated to be elastic in both our dynamic models, we consistently find PED is more inelastic than the OLS.

In both dynamic models we utilize more instruments than endogenous regressors which causes our models to be over identified. We use the Sargan-Hansen J test to see if additional instruments are necessary. The null hypothesis states that the instruments are valid meaning they are not correlated with the error terms in the structural model. Being that the effects of each individual hurricane are highly correlated with one another, it is not surprising the J-stat is small, which implies a rejection of the null hypothesis. Though the findings may not be statistically persuasive, it is reassuring that the direction of the bias is consistent across all identification strategies.

Table 3.4: First Stage (Binary Indicator Variable (BIV) Model): Column (1) represents the baseline model with out fixed effects. Column (2) incorporates month fixed effects. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	(1)	(2)
	Log Market Quantity (10K LBS)	Log Market Quantity (10K LBS)
Hurricane Indicator (Binary)	-0.158***	-0.286***
	(-11.39)	(-22.77)
Observations	195679	195679
R squared	0.000662	0.333
Month FE	0	1

Table 3.5: Second Stage (Binary Indicator Variable (BIV) Model): Column (1) represents the standard OLS model that does not control for endogeneity. Column (2) is our 2SLS model with out fixed effects. Column (3) incorporates month fixed effects. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	(1)	(2)	(3)
	Log Price per LBS	Log Price per LBS	Log Price per LBS
Log Market Quantity (10K LBS)	-0.00367*	-3.021***	-1.455***
	(-1.70)	(-11.00)	(-19.04)
Observations	195679	195679	195679
R squared	0.0885	.	.
First stage F		129.7	518.4
OLS Model	1	0	0
Month FE	1	0	1

Table 3.6: First Stage (Three Instrumental Variables (3IV) Model Results): Column (1) represents the baseline model with out fixed effects. Column (2) incorporates month fixed effects. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	(1)	(2)
	Log Market Quantity (10K LBS)	Log Market Quantity (10K LBS)
KILO	0.263***	0.115***
	(10.81)	(5.46)
IGNACIO	-0.172***	-0.201***
	(-6.50)	(-9.05)
JIMENA	-0.632***	-0.606***
	(-18.50)	(-21.65)
Observations	195679	195679
R squared	0.00406	0.337
Month FE	0	1

Table 3.7: Second Stage (Three Instrumental Variables (3IV) Model Results): Column (1) represents the standard OLS model that does not control for endogeneity. Column (2) is our 2SLS model with out fixed effects. Column (3) incorporates month fixed effects. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	(1)	(2)	(3)
	Log Price per LBS	Log Price per LBS	Log Price per LBS
Log Market Quantity (10K LBS)	-0.00367*	-0.590***	-0.548***
	(-1.70)	(-20.87)	(-24.35)
Observations	195679	195679	195679
R squared	0.0885	.	.
First stage F		282.7	296.0
J-Stat		1.90e-244	2.32e-131
OLS Model	1	0	0
Month FE	1	0	1

Table 3.8: First Stage (14 Instrumental Variables (14IV) Model Results): Column (1) represents the baseline model with out fixed effects. Column (2) incorporates month fixed effects. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	(1)	(2)
	Log Market Quantity (10K LBS)	Log Market Quantity (10K LBS)
day_00	0	0
	(.)	(.)
day_01	-0.436***	-0.581***
	(-8.95)	(-14.48)
day_03	0.810***	0.665***
	(23.67)	(23.32)
day_04	-0.109***	-0.253***
	(-3.13)	(-8.75)
day_05	0.589***	0.444***
	(14.33)	(13.08)
day_06	0.178***	0.0335
	(4.46)	(1.01)
day_08	-1.636***	-1.781***
	(-30.27)	(-40.14)
day_10	-3.008***	-3.152***
	(-51.02)	(-65.27)
day_11	0.150**	0.133**
	(1.98)	(2.14)
day_12	-0.650***	-0.668***
	(-14.34)	(-17.73)
day_14	0.685***	0.668***
	(14.87)	(17.47)
Observations	195679	195679
R squared	0.0241	0.357
First stage F		
Month FE	0	1

Table 3.9: Second Stage (14 Instrumental Variables (14IV) Model Results): Column (1) represents the standard OLS model that does not control for endogeneity. Column (2) is our 2SLS model with out fixed effects. Column (3) incorporates month fixed effects. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	(1)	(2)	(3)
	Log Price per LBS	Log Price per LBS	Log Price per LBS
Log Market Quantity (10K LBS)	-0.00367*	-0.215***	-0.211***
	(-1.70)	(-36.32)	(-38.09)
Observations	195679	195679	195679
R squared	0.0885	.	0.0458
First stage F		4230.8	34599.5
J-Stat		0	0
OLS Model	1	0	0
Month FE	1	0	1

3.5.2 Accounting for Closures

Quota based management for bigeye tuna was first introduced to the United States in the early 2000s as a means to control harvest in the Western and Central Pacific Fisheries Commission (WCPFC) (Ayers et al., 2018). Annual quotas are set by assessing species stock and negotiations between members of the Regional Fishery Management Organizations (RFMO). Six out of 27 WCPFC members are subject to quotas; the United States being one of them. The Pacific Ocean falls under two jurisdictions, Western and Eastern, both of which abide by different quota limits and regulations. During a closure, there are exceptions that allow certain vessels to continue fishing operations, but for most vessels, once a quota is met, fishing activity must cease.

In 2015 the pacific longline fishery experienced an *effective closure* in which both sides of the pacific (east and west) were closed. Based on the different regulations enforced on each side of the pacific, all single permitted US vessels must cease fishing on the western pacific and all vessels longer than 24 meters in length must cease fishing on in the eastern pacific. Once a closure is in effect, these vessels have 14 days to land any bigeye caught. Despite an effective closure taking place, a regulation loophole still allows dual permitted vessels to continue fishing operations and attribute their catch to American Samoa. In addition, vessels longer than 24 meters in length can shift effort and remain fishing operations in

western pacific waters.

The Western Pacific closed from August 5, 2015 to October 9, 2015 while the Eastern Pacific was closed from August 12, 2015 to December 31, 2015 (Ayers et al., 2018). The effective closure lasted between August 12, 2015 to October 9, 2015. Considering the hurricane days were completely engulfed in the middle of the two closures we suspect our results will not change. Nonetheless, as a robustness checks we control for closures by flagging any day in which a closure was in effect (either west, east, or both). The *Closure Indicator* variable takes a value of 1 if day t experiences at least one closure type and zero otherwise. Table (3.10) and Table (3.11) represents first and second stage results respectively. Additional closure specifications can be found in the Appendix.

We run all three models (BIV, 3IV, and 14IV) with month fixed effects and closure day controls. Table (3.10) show the frist stage results from each model. As a means to condense the table, we only display coefficients for hurricane day 1 ($day_0 1$), hurricane day 6 ($day_0 6$), and hurricane day 14 ($day_1 4$). We find strong correlation between the instrument and log landings for the BIV model and weak correlation for the 3IV model and 14IV model. Table (3.11) compares the three IV models (Columns (2), (3), and (4)) with the standard OLS (Column (1)). Results are consistent with our main specification and all IV models consistently estimate a more inelastic demand compared to OLS.

Table 3.10: First Stage (Closures): The Closure Indicator variable controls for any day that experienced at least one closure type. Column (1) represents the first stage BIV, Column (2) the first stage 3IV, and Column (3) the first stage 14IV. Month fixed effects are used across all specifications. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	(1)	(2)	(3)
	Model BIV	Model 3IV	Model 14IV
Hurricane Indicator (Binary)	-0.366***		
	(-28.66)		
Closure Indicator	0.575***	0.594***	0.571***
	(32.32)	(33.36)	(32.58)
KILO		0.00869	
		(0.41)	
IGNACIO		-0.202***	
		(-9.12)	
JIMENA		-0.598***	
		(-21.42)	
day_01			-0.682***
			(-17.00)
day_06			-0.0678**
			(-2.05)
day_14			0.668***
			(17.52)
Observations	195679	195679	195679
Month FE	1	1	1

Table 3.11: Second Stage (Closures): The Closure Indicator variable controls for any day that experienced at least one closure type. Column (1) represents the standard OLS, Column (2) first stage BIV, Column (3) the first stage 3IV, and Column (4) the first stage 14IV. Month fixed effects are used across all specifications. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	(1) OLS	(2) BIV	(3) 3IV	(4) 14IV
Log Market Quantity (10K LBS)	-0.00585***	-1.074***	-0.498***	-0.202***
	(-2.70)	(-21.41)	(-25.95)	(-37.48)
Closure Indicator	0.275***	0.783***	0.516***	0.378***
	(16.37)	(22.61)	(24.35)	(23.52)
Observations	195679	195679	195679	195679
First stage F		821.3	381.6	126125.5
J-Stat			5.36e-94	0
Month FE	1	1	1	1

3.6 Discussion

Bigeye tuna accounts for the largest market share in terms of landings and revenue for the state of Hawaii. Current management practices strive to ensure both biological and economic viability, though individual incentives may not yield maximum potential revenue due to periods of flooding market supply. The proposed study estimates the inverse price elasticity of demand to explore if revenue gains can be made through fisherman cooperation.

Using the three category 4 hurricanes that simultaneously entered the Pacific in 2015, we isolate exogenous shifts in landings to obtain an unbiased estimate of the inverse price elasticity of demand. Running a simple ordinary least squares (OLS) model, we estimate an elastic demand. Despite the congruity between our OLS findings and estimations of PED done by previous studies, the OLS coefficient is biased due to endogeneity. The bias driving an elastic estimate could be caused by simultaneous shifts of both supply and demand by factors that are not captured in our model. For example, Hawaii buyers track conditions in the continental US due to the export market. If New York is experiencing a snowstorm that limits imports, Hawaii wholesalers are less likely to buy during a given market day.

Fishermen may also respond to this anticipated decrease in demand by waiting to land their catch. Regressing price onto quantity using a simple OLS would lead to a biased estimate because the model is inadequately isolating the price response with respect to a change in demand. Instead, price is being driven exogenously by external factors that are not being accounted for.

An inelastic estimate suggests fisherman can be more profitable by scaling back production. Higher profits could be channeled in two forms: increased market prices and a reduction in effort. By the law of demand, lowering market quantity would be coupled with an increase of per unit price. Reduced effort would occur in the short run because aggregate landings could not exceed a certain amount thus, we would expect operational cost to decrease insuring higher profit margins, assuming all else equal (Bertignac et al., 2000). In theory, catch per unit effort may also increase by allowing the species time to spawn and mature (Kompas et al., 2006).

There is still work to be done in this area that is beyond the scope of the proposed study. Though an inelastic estimate implies higher profits can be attained by reducing supply, in reality, the Hawaii tuna market is integrated on a global scale. Our model only allows price and quantity to vary and all other factors are held constant. We did not consider the imports market or cross-price elasticities of substitute goods. Grocery stores and restaurants have a diverse consumer base in which demand spans over a wide range of products, and, for some retail buyers, imports are deemed as perfect substitutes for fresh tuna. In addition, a retraction in supply can have downstream effects on the broader market for tuna. Wholesalers might suspect there exists some upper bound that price cannot exceed otherwise tuna will be too expensive for retail buyers. Though it might seem their demand is inelastic to price, it could be, once this price cap is reached, buyers will shift their preferences and substitute fresh tuna with imports. Manipulating market supply might increase revenues in the short run but can adversely hurt the fishery as the import market grows. Understanding how these markets are integrated and estimating the cross- price elasticities for other substitute goods needs to be explored before any recommendations on optimal market supply can be made.

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Appendix A

Chapter One Appendix

A.1 Additional Tables

Supplemental tables that summarize the graphical representations of our regression results are provided in Tables (A.1), (A.2), (A.3), (A.4) and (A.5). Tables (A.1), (A.2), and (A.3) represent the 100-, 200-, and 300- mile region radius for the vessel and time fixed effects regressions ('Captain/Time FE'). Tables (A.4) and (A.5) summarize regression results from our 'Kitchen Sink FE' models at the 200- and 300-mile specifications where captain fixed effects, time trends, and various gear types are controlled for. Each column represents species specific regression results where the *Distance Dummy* is our coefficient of interest. This estimates the effect of fishing in the 'near' region relative to the 'far' region, after PMNM was expanded.

Because we arbitrarily set our region-radii at the 100-, 200-, and 300- mile specification, our results could suffer from sampling biased. As a robustness check, we run a continuous distance specification by bounding the fishing area to represent 400 miles from the MPA boarder and define our *Distance Dummy* to be the miles away from the PMNM boundary. In addition to the 'Kitchen-Sink' model, we provide the regression results for the 'No FE', 'Captain/Time FE', and 'Seamount FE' model in Tables (A.6), (A.7), and (A.8). These tables are the tabular form of the regression results displayed in Figure (1.5). The coefficient of interest, *Distance Dummy*, now measures the effect of fishing further away from the MPA boarder, after the expansion. Coefficient interpretation is now reversed, a negative estimate will indicate a positive spillover presence.

Table A.1: Cap MonthYr (100 Mile Region-Radius): Heterogeneity across captain efficiency and natural time trends are controlled for. Each successive column displays results for each species group Bigeye, Yellowfin, All, and Other, using a difference-in-difference regression. DID coefficients measure the effect of fishing close to PMNM after PMNM was expanded in the 2016. The sample runs from January 6, 2010 to January 11, 2020. *p<0.1; **p<0.05; ***p<0.01 Heteroskedasticity-robust standard errors presented in parentheses.

	Bigeye	Yellowfin	All	Other
	(1)	(2)	(3)	(4)
Diff in Diff	0.111	0.533**	0.073*	0.038
	(0.072)	(0.222)	(0.040)	(0.045)
Expansion Dummy	−0.262	−2.589***	−0.655***	−0.639***
	(0.181)	(0.763)	(0.093)	(0.148)
Distance Dummy	−0.031	−0.027	−0.004	0.004
	(0.036)	(0.105)	(0.025)	(0.030)
Observations	5,665	5,665	5,665	5,663
R^2	0.137	0.169	0.147	0.150

Table A.2: Cap MonthYr (200 Mile Region-Radius): Heterogeneity across captain efficiency and natural time trends are controlled for. Each successive column displays results for each species group Bigeye, Yellowfin, All, and Other, using a difference-in-difference regression. DID coefficients measure the effect of fishing close to PMNM after PMNM was expanded in the 2016. The sample runs from January 6, 2010 to January 11, 2020. *p<0.1; **p<0.05; ***p<0.01 Heteroskedasticity-robust standard errors presented in parentheses.

	Bigeye	Yellowfin	All	Other
	(1)	(2)	(3)	(4)
Diff in Diff	0.086*	0.697***	0.040	−0.003
	(0.050)	(0.182)	(0.029)	(0.035)
Expansion Dummy	−0.360***	−3.033***	−0.440***	−0.330***
	(0.112)	(0.741)	(0.047)	(0.084)
Distance Dummy	−0.067**	0.170**	0.005	0.014
	(0.032)	(0.068)	(0.018)	(0.023)
Observations	15,455	15,455	15,455	15,452
R^2	0.110	0.128	0.131	0.126

Table A.3: Cap MonthYr (300 Mile Region-Radius): Heterogeneity across captain efficiency and natural time trends are controlled for. Each successive column displays results for each species group Bigeye, Yellowfin, All, and Other, using a difference-in-difference regression. DID coefficients measure the effect of fishing close to PMNM after PMNM was expanded in the 2016. The sample runs from January 6, 2010 to January 11, 2020. *p<0.1; **p<0.05; ***p<0.01 Heteroskedasticity-robust standard errors presented in parentheses.

	Bigeye	Yellowfin	All	Other
	(1)	(2)	(3)	(4)
Diff in Diff	0.041	0.302**	0.029	0.014
	(0.042)	(0.123)	(0.025)	(0.029)
Expansion Dummy	−0.909***	−3.684***	−0.526***	−0.300***
	(0.163)	(0.535)	(0.056)	(0.076)
Distance Dummy	−0.055*	0.304***	−0.025*	−0.032*
	(0.030)	(0.070)	(0.015)	(0.018)
Observations	23,280	23,280	23,280	23,277
R^2	0.097	0.133	0.126	0.119

Table A.4: Kitchen Sink (200 Mile Region-Radius): Heterogeneity across captain efficiency, natural time trends, seamount sets, and various gear are controlled for. Each successive column displays results for each species group Bigeye, Yellowfin, All, and Other, using a difference-in-difference regression. DID coefficients measure the effect of fishing close to PMNM after PMNM was expanded in the 2016. The sample runs from January 6, 2010 to January 11, 2020. *p<0.1; **p<0.05; ***p<0.01 Heteroskedasticity-robust standard errors presented in parentheses.

	Bigeye	Yellowfin	All	Other
	(1)	(2)	(3)	(4)
Diff in Diff	0.078	0.687***	0.029	−0.017
	(0.049)	(0.177)	(0.030)	(0.035)
Expansion Dummy	−0.340***	−3.029***	−0.367***	−0.239**
	(0.089)	(0.740)	(0.055)	(0.102)
Distance Dummy	−0.063**	0.193***	0.005	0.013
	(0.030)	(0.062)	(0.019)	(0.023)
Observations	15,195	15,195	15,195	15,192
R^2	0.117	0.142	0.140	0.132

Table A.5: Kitchen Sink (300 Mile Region-Radius): Heterogeneity across captain efficiency, natural time trends, seamount sets, and various gear are controlled for. Each successive column displays each species group Bigeye, Yellowfin, All, and Other, using a difference-in-difference regression. DID coefficients measure the effect of fishing close to PMNM after PMNM was expanded in the 2016. The sample runs from January 6, 2010 to January 11, 2020. *p<0.1; **p<0.05; ***p<0.01 Heteroskedasticity-robust standard errors presented in parentheses.

	Bigeye	Yellowfin	All	Other
	(1)	(2)	(3)	(4)
Diff in Diff	0.031	0.293**	0.020	0.006
	(0.043)	(0.123)	(0.025)	(0.029)
Expansion Dummy	−0.875***	−3.698***	−0.470***	−0.237***
	(0.163)	(0.537)	(0.044)	(0.070)
Distance Dummy	−0.044	0.342***	−0.021	−0.030*
	(0.029)	(0.060)	(0.015)	(0.018)
Observations	22,881	22,881	22,881	22,878
R^2	0.102	0.141	0.135	0.126

Table A.6: No FE (Continuous Distance): Our distance variable is defined as 'miles away from MPA boarder'. Each successive column displays results for each species group Bigeye, Yellowfin, All, and Other, using a difference-in-difference regression. DID coefficients measure the effect of fishing close to PMNM after PMNM was expanded in the 2016. The sample runs from January 6, 2010 to January 11, 2020. *p<0.1; **p<0.05; ***p<0.01 Heteroskedasticity-robust standard errors presented in parentheses.

	Bigeye	Yellowfin	All	Other
	(1)	(2)	(3)	(4)
Diff in Diff	−0.001***	−0.003***	−0.0003***	−0.00002
	(0.0001)	(0.0004)	(0.0001)	(0.0001)
Expansion Dummy	0.247***	1.698***	0.032**	−0.105***
	(0.034)	(0.101)	(0.016)	(0.016)
Distance Dummy	0.0002**	−0.001***	−0.0001***	−0.0001***
	(0.0001)	(0.0002)	(0.00004)	(0.00004)
Observations	16,571	16,571	16,571	16,568
R^2	0.003	0.060	0.005	0.014

Table A.7: Cap MonthYr (Continuous Distance): Our distance variable is defined as 'miles away from MPA boarder'. We control for heterogeneity in captain efficiency and natural time trends. Each successive column displays results for each species group Bigeye, Yellowfin, All, and Other, using a difference-in-difference regression. DID coefficients measure the effect of fishing close to PMNM after PMNM was expanded in the 2016. The sample runs from January 6, 2010 to January 11, 2020. *p<0.1; **p<0.05; ***p<0.01 Heteroskedasticity-robust standard errors presented in parentheses.

	Bigeye	Yellowfin	All	Other
	(1)	(2)	(3)	(4)
Diff in Diff	−0.0005**	−0.004***	−0.0002	0.0001
	(0.0002)	(0.001)	(0.0001)	(0.0002)
Expansion Dummy	−0.199**	−2.034***	−0.421***	−0.392***
	(0.084)	(0.651)	(0.046)	(0.089)
Distance Dummy	0.0003***	−0.001***	−0.0001	−0.0002*
	(0.0001)	(0.0003)	(0.0001)	(0.0001)
Observations	16,571	16,571	16,571	16,568
R^2	0.113	0.123	0.127	0.122

Table A.8: Seamounts (Continuous Distance): Our distance variable is defined as 'miles away from MPA boarder'. We control for heterogeneity in captain efficiency, natural time trends, and seamount sets. Each successive column displays results for each species group Bigeye, Yellowfin, All, and Other, using a difference-in-difference regression. DID coefficients measure the effect of fishing close to PMNM after PMNM was expanded in the 2016. The sample runs from January 6, 2010 to January 11, 2020. *p<0.1; **p<0.05; ***p<0.01 Heteroskedasticity-robust standard errors presented in parentheses.

	Bigeye	Yellowfin	All	Other
	(1)	(2)	(3)	(4)
Diff in Diff	−0.0005**	−0.003***	−0.0002	0.0001
	(0.0002)	(0.001)	(0.0001)	(0.0002)
Expansion Dummy	−0.202**	−2.039***	−0.422***	−0.393***
	(0.085)	(0.655)	(0.045)	(0.089)
Distance Dummy	0.0003***	−0.001***	−0.0001	−0.0002*
	(0.0001)	(0.0003)	(0.0001)	(0.0001)
Observations	16,571	16,571	16,571	16,568
R^2	0.114	0.123	0.127	0.122

A.2 Logbook Data

In addition to the observer data set, NMFS also manages the *logbook data*, data obtained from captains self-reporting fishing activity in the form of logbooks. This data set can be less reliable than that of the observer data because of the self-reporting nature of the data collection. Moreover, logbook data does not provide as much detail on fishing methods (e.g gear type, bait used, etc). Despite the uncertainty around data entries and lack of information on fishing methods, the logbook data is larger than the observer data set. The logbook data covers every fishing trip made whereas the observer data set only covers 20% of all deep-set fishing expeditions.

To compare our results against a larger data set, we run our main specification ('Captain/Time FE') for 100-, 200-, and 300-mile region-radii using the logbook data, in tables (A.9), (A.10), and (A.11) respectively, where bigeye, yellowfin, all-species, and other are reported in Columns (1), (2), (3), and (4) respectively. Results consistently show a positive statistically significant spillover for yellowfin across all region-radii.

Table A.9: Logbook Data (100 Mile Region-Radius): Results from Cap MonthYr Model are displayed where heterogeneity across captain efficiency and natural time trends are controlled for. Each successive column displays results for each species group Bigeye, Yellowfin, All, and Other, using a difference-in-difference regression. DID coefficients measure the effect of fishing close to PMNM after PMNM was expanded in the 2016. The sample runs from January 6, 2010 to January 11, 2020. *p<0.1; **p<0.05; ***p<0.01 Heteroskedasticity-robust standard errors presented in parentheses.

	BET	YF	ALL	OTHER
	(1)	(2)	(3)	(4)
Diff in Diff	0.131^{***}	0.103	0.033	-0.017
	(0.035)	(0.090)	(0.025)	(0.028)
Expansion Dummy	-0.155^{**}	-1.739^{*}	-0.364^{**}	-0.319^{**}
	(0.077)	(1.008)	(0.164)	(0.146)
Distance Dummy	-0.077^{***}	0.128^{**}	0.009	0.035^{*}
	(0.023)	(0.051)	(0.017)	(0.020)
Observations	23,131	23,131	23,131	23,035
R^2	0.127	0.147	0.099	0.151

Table A.10: Logbook Data (200 Mile Region-Radius): Results from Cap MonthYr Model are displayed where heterogeneity across captain efficiency and natural time trends are controlled for. Each successive column displays results for each species group Bigeye, Yellowfin, All, and Other, using a difference-in-difference regression. DID coefficients measure the effect of fishing close to PMNM after PMNM was expanded in the 2016. The sample runs from January 6, 2010 to January 11, 2020. *p<0.1; **p<0.05; ***p<0.01 Heteroskedasticity-robust standard errors presented in parentheses.

	BET	YF	ALL	OTHER
	(1)	(2)	(3)	(4)
Diff in Diff	0.105^{***}	0.310^{***}	0.026	-0.042^{**}
	(0.038)	(0.081)	(0.018)	(0.018)
Expansion Dummy	-0.210	-1.007^{*}	-0.345^{***}	-0.342^{***}
	(0.218)	(0.587)	(0.127)	(0.131)
Distance Dummy	-0.063^{**}	0.112^{*}	-0.003	0.016
	(0.025)	(0.059)	(0.012)	(0.013)
Observations	77,354	77,354	77,354	77,032
R^2	0.078	0.106	0.085	0.114

Table A.11: Logbook Data (300 Mile Region-Radius): Results from Cap MonthYr Model are displayed where heterogeneity across captain efficiency and natural time trends are controlled for. Each successive column displays results for each species group Bigeye, Yellowfin, All, and Other, using a difference-in-difference regression. DID coefficients measure the effect of fishing close to PMNM after PMNM was expanded in the 2016. The sample runs from January 6, 2010 to January 11, 2020. *p<0.1; **p<0.05; ***p<0.01 Heteroskedasticity-robust standard errors presented in parentheses.

	BET	YF	ALL	OTHER
	(1)	(2)	(3)	(4)
Diff in Diff	0.101^{***}	0.124^{**}	0.038^{***}	0.002
	(0.023)	(0.061)	(0.013)	(0.016)
Expansion Dummy	-0.199	-1.264^{**}	-0.432^{**}	-0.473
	(0.143)	(0.540)	(0.205)	(0.294)
Distance Dummy	-0.083^{***}	0.284^{***}	-0.043^{***}	-0.051^{***}
	(0.022)	(0.052)	(0.012)	(0.013)
Observations	120,622	120,622	120,622	120,161
R^2	0.075	0.111	0.091	0.118

Appendix B

Chapter Two Appendix

In addition to the western 2016, eastern 2017, and effective 2015 closures included in the main text, we provide results from each individual closure. Each subsection represents one individual closure and is organized as followed. We first display time trend plots that compare longitude and catch 30 days pre and 30 days post a closure start and end. Each variable is standardized based off of the pre-closure average and standard deviation such that graphical observations are the number of standard deviations away from the pre-closure average. Time trend figures are followed by regression results for the Temporal DID approach for relative longitude and catch, Within-Year DID approach, and the Triple DID approach. *Relative Longitude* is defined as the difference between Honolulu (HNL) longitude coordinates and *begin set* longitude coordinates such that negative values indicate a more western movement and positive values indicate a more eastern relative to HNL port.

B.1 Western Closures

Results for the 2009, 2010, 2015, and 2017 western closures are given in Sections B.1.1, B.1.2, B.1.3, and B.1.4 respectively.

When defining treatment and control group over closure years instead of fishery subgroups (Temporal Approach), we find the following. The earlier western closures (2009 and 2010) appeared to be more successful in reducing catch across fishery subgroups relative to the recent closures (2015, 2016, and 2017). From 2009 to 2015 there was a consistent

eastern shift in set location across all fishery subgroups as shown in Tables (B.1), (B.5), and (B.9) followed with a negative to inconclusive effect on catch (Tables (B.2), (B.6), and (B.10). The first Pacific closure in history occurred in 2009. Though the duration of the closure was short, only lasting 5 calendar days, the fishery experienced a shock and catch decreased across all fishery subgroups, refer to Table (B.2). By 2015, dual permitted vessels seem to have adapted and observe a weakly positive increase in catch, refer to Table (B.10), yet location of fishing activity no different than in non-closure years. First signs of a pollution haven, or the pollution havens hypothesis (PHH), becomes evident in 2016 and in 2017 where we see an eastern displacement of fishing effort accompanied by a statistically significant increase in catch for the Sngl/<24 group. Table (B.13) estimate an eastern movement while Table (B.14) estimates an increase in catch during the 2017 closure. These results support the PHH for the 2017 closure; evidence during the 2016 closure can be found in the main text. The only subgroup that is consistently hurt by western closures are the Sngl/>24 vessels as shown by the reduced catch levels (Tables (B.2), (B.6), (B.10), (B.14)).

Defining our treatment group as all single permitted vessels in our Within-Year DID, we consistently measure a more eastern movement as compared to the control group (dual permitted vessels). Catch decreases for the initial closures but, by 2016, captains have adapted and catch increases relative to the dual permitted. Results are consistent with the Triple DID model which finds catch weakly increased for the 2016 and 2017 closures.

B.1.1 West 2009

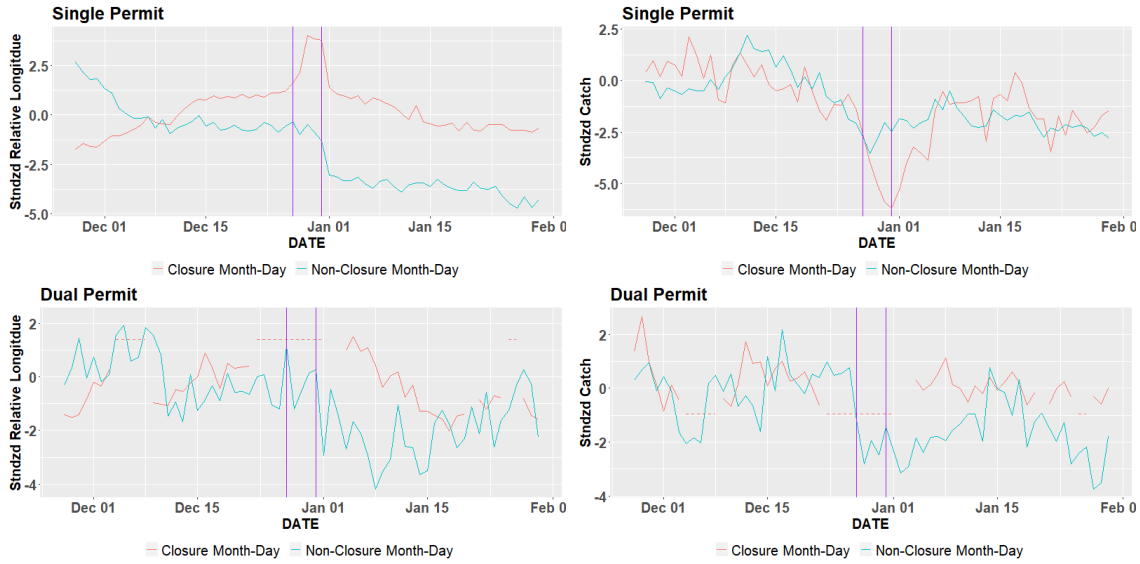

Figure B.1: Comparing Fishing Conditions for the 2009 Western Closure: All time series include fishing activities 30 days pre and 30 days post closure start and end respectively. Left panel represents longitude relative to HNL port and the right panel represents catch.

Table B.1: Temporal DID (West 2009 Closure) Longitude Relative to HNL: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	0.422^{**}	-1.472^{***}	1.559^{***}	-0.252
	(0.173)	(0.395)	(0.084)	(0.192)
Closure Month−Day	0.455	-1.784^{***}	-0.186^{**}	-0.460^{**}
	(0.318)	(0.357)	(0.091)	(0.180)
Diff in Diff	-0.594^{*}	12.626^{***}	4.804^{***}	11.220^{***}
	(0.356)	(0.515)	(0.555)	(0.777)
Observations	7,235	2,117	65,967	14,834
R^2	0.001	0.013	0.009	0.012

Table B.2: Temporal DID (West 2009 Closure) Catch: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	−1.377***	−5.200***	−1.829***	−1.624***
	(0.313)	(0.482)	(0.082)	(0.195)
Closure Month−Day	−0.155	1.453	0.587***	0.342
	(0.399)	(1.081)	(0.137)	(0.326)
Diff in Diff	−4.604***	−0.875	−0.495	−1.065
	(0.495)	(1.819)	(0.449)	(0.830)
Observations	7,235	2,117	65,967	14,834
R^2	0.002	0.013	0.005	0.003

Table B.3: Within-Year DID (West 2009 Closure): The treatment group is defined as single permitted vessels. The control group is defined as dual permitted vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Days	10.826***	−1.737
	(0.187)	(1.427)
Treatment Group	−0.500***	−0.958***
	(0.171)	(0.279)
Diff in Diff	−4.950***	1.678
	(0.506)	(1.475)
Observations	6,746	6,746
R^2	0.034	0.002

Table B.4: Triple DID (West 2009 Closure): The treatment group is defined as single permitted vessels. The control group is defined as dual permitted vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Year	-1.535^{***}	-1.191^{***}
	(0.158)	(0.274)
Closure Days	-1.599^{***}	0.922^{**}
	(0.248)	(0.398)
Treatment Group	-1.176^{***}	-1.109^{***}
	(0.039)	(0.048)
Triple Diff in Diff	-4.259^{***}	1.320
	(0.569)	(1.532)
Observations	456,746	456,746
R^2	0.004	0.002

B.1.2 West 2010

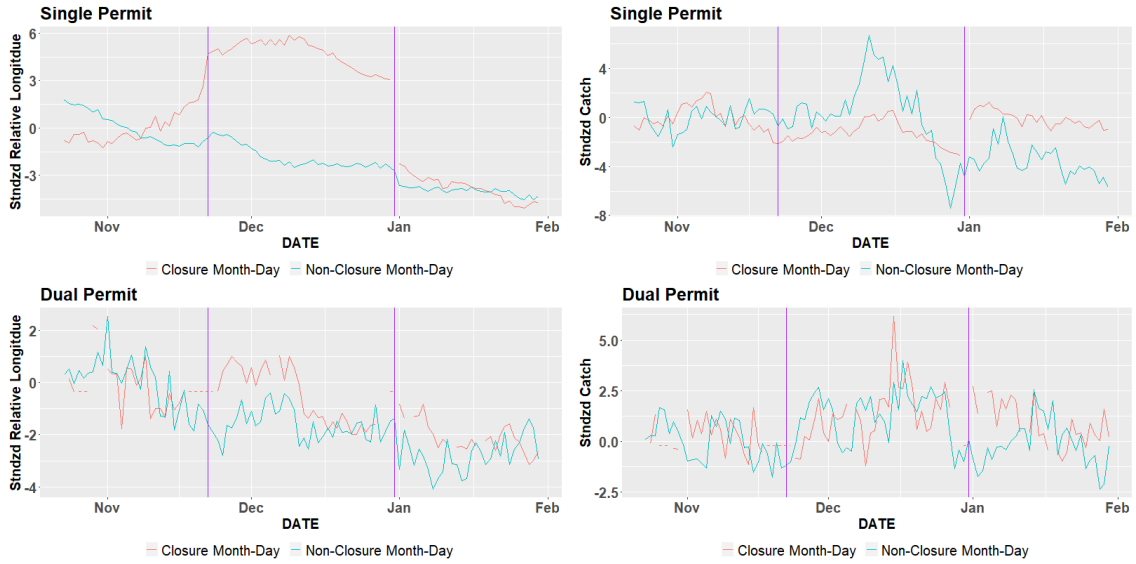

Figure B.2: Comparing Fishing Conditions for the 2010 Western Closure: All time series include fishing activities 30 days pre and 30 days post closure start and end respectively. Left panel represents longitude relative to HNL port and the right panel represents catch.

Table B.5: Temporal DID (West 2010 Closure) Longitude Relative to HNL: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	-0.591^{**}	-4.223^{***}	-0.201^{*}	0.603^{***}
	(0.264)	(0.309)	(0.103)	(0.225)
Closure Month−Day	-0.110	-2.154^{***}	-0.792^{***}	-1.155^{***}
	(0.109)	(0.243)	(0.036)	(0.079)
Diff in Diff	2.205^{***}	0.665	12.887^{***}	13.312^{***}
	(0.410)	(0.492)	(0.125)	(0.262)
Observations	11,542	3,285	105,350	24,678
R^2	0.003	0.046	0.081	0.115

Table B.6: Temporal DID (West 2010 Closure) Catch: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	0.980**	−0.446	−0.221*	−0.070
	(0.493)	(0.949)	(0.126)	(0.257)
Closure Month−Day	0.298*	1.176***	0.252***	0.191*
	(0.167)	(0.366)	(0.049)	(0.112)
Diff in Diff	1.082	−0.863	−0.969***	−1.118***
	(0.828)	(1.313)	(0.209)	(0.403)
Observations	11,542	3,285	105,350	24,678
R^2	0.002	0.004	0.001	0.001

Table B.7: Within-Year DID (West 2010 Closure): The treatment group is defined as single permitted vessels. The control group is defined as dual permitted vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Days	1.248***	1.116
	(0.346)	(0.703)
Treatment Group	0.228	−1.800***
	(0.231)	(0.451)
Diff in Diff	10.862***	−1.864**
	(0.362)	(0.725)
Observations	8,868	8,868
R^2	0.470	0.011

Table B.8: Triple DID (West 2010 Closure): The treatment group is defined as single permitted vessels. The control group is defined as dual permitted vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Year	-2.325^{***}	1.196^{***}
	(0.216)	(0.440)
Closure Days	-1.466^{***}	0.832^{***}
	(0.083)	(0.128)
Treatment Group	-1.181^{***}	-1.092^{***}
	(0.043)	(0.051)
Triple Diff in Diff	11.120^{***}	-1.928^{***}
	(0.373)	(0.737)
Observations	459,442	459,442
R^2	0.023	0.003

B.1.3 West 2015

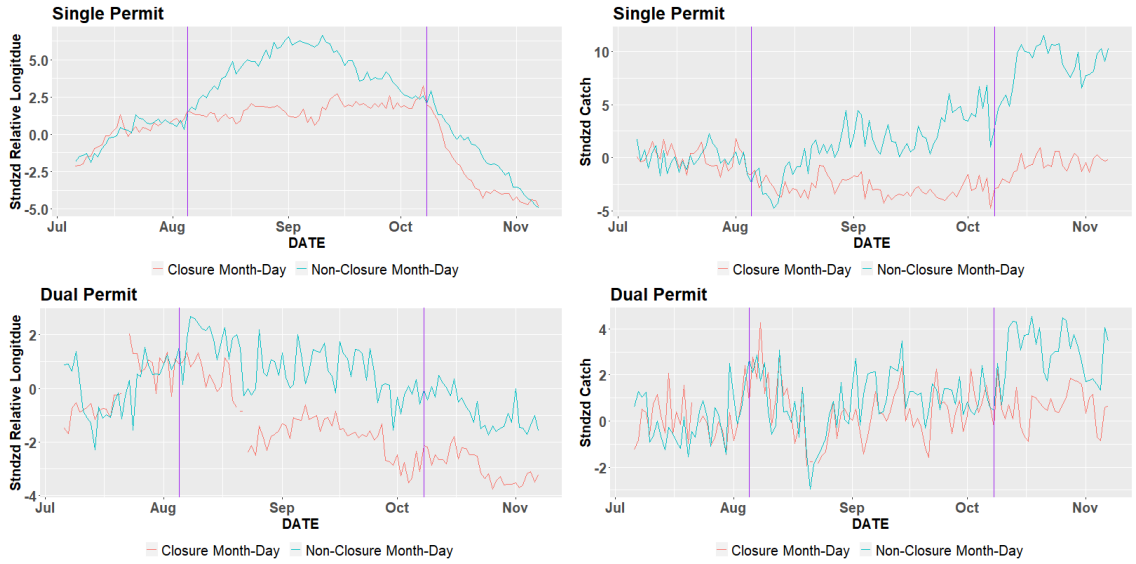

Figure B.3: Comparing Fishing Conditions for the 2010 Western Closure: All time series include fishing activities 30 days pre and 30 days post closure start and end respectively. Left panel represents longitude relative to HNL port and the right panel represents catch.

Table B.9: Temporal DID (West 2015 Closure) Longitude Relative to HNL: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	0.603*	−3.504***	4.527***	2.901***
	(0.317)	(0.445)	(0.120)	(0.246)
Closure Month−Day	1.753***	1.265***	1.205***	1.827***
	(0.133)	(0.333)	(0.041)	(0.080)
Diff in Diff	1.120**	−0.590	5.971***	−0.788
	(0.505)	(0.568)	(0.142)	(0.590)
Observations	10,924	2,698	112,765	29,922
R^2	0.022	0.057	0.098	0.021

Table B.10: Temporal DID (West 2015 Closure) Catch: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	1.305***	0.992	2.260***	2.359***
	(0.388)	(0.671)	(0.161)	(0.359)
Closure Month−Day	0.085	−0.392	−0.297***	−0.129
	(0.195)	(0.445)	(0.052)	(0.119)
Diff in Diff	1.078*	0.453	−0.600**	−4.294***
	(0.644)	(0.906)	(0.234)	(0.569)
Observations	10,924	2,698	112,765	29,922
R^2	0.004	0.003	0.004	0.002

Table B.11: Within-Year DID (West 2015 Closure): The treatment group is defined as single permitted vessels. The control group is defined as dual permitted vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Days	1.706***	0.676
	(0.351)	(0.478)
Treatment Group	3.835***	0.143
	(0.267)	(0.350)
Diff in Diff	5.535***	−1.837***
	(0.375)	(0.524)
Observations	11,247	11,247
R^2	0.255	0.003

Table B.12: Triple DID (West 2015 Closure): The treatment group is defined as single permitted vessels. The control group is defined as dual permitted vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Year	1.912***	0.982***
	(0.249)	(0.323)
Closure Days	3.940***	−0.392***
	(0.103)	(0.146)
Treatment Group	−1.423***	−1.115***
	(0.041)	(0.051)
Triple Diff in Diff	5.170***	−1.937***
	(0.390)	(0.545)
Observations	461,445	461,445
R^2	0.092	0.003

B.1.4 West 2017

Figure B.4: Comparing Fishing Conditions for the 2017 Western Closure: All time series include fishing activities 30 days pre and 30 days post closure start and end respectively. Left panel represents longitude relative to HNL port and the right panel represents catch.

Table B.13: Temporal DID (West 2017 Closure) Longitude Relative to HNL: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	-0.629^{**}	-0.434	2.737^{***}	1.075^{***}
	(0.245)	(0.374)	(0.117)	(0.255)
Closure Month−Day	1.116^{***}	1.256^{***}	0.966^{***}	1.155^{***}
	(0.162)	(0.403)	(0.047)	(0.092)
Diff in Diff	-2.111^{***}	-5.855^{***}	6.958^{***}	2.972^{***}
	(0.498)	(0.572)	(0.154)	(0.647)
Observations	8,663	2,235	89,790	23,917
R^2	0.011	0.076	0.075	0.011

Table B.14: Temporal DID (West 2017 Closure) Catch: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	−1.237***	−1.433***	1.069***	0.296
	(0.295)	(0.458)	(0.139)	(0.306)
Closure Month−Day	−0.103	−0.400	−0.134**	0.128
	(0.236)	(0.592)	(0.060)	(0.133)
Diff in Diff	0.623	−0.247	0.559**	−2.081***
	(0.494)	(0.750)	(0.226)	(0.535)
Observations	8,663	2,235	89,790	23,917
R^2	0.001	0.008	0.002	0.0004

Table B.15: Within-Year DID (West 2017 Closure): The treatment group is defined as single permitted vessels. The control group is defined as dual permitted vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Days	−2.497***	0.035
	(0.324)	(0.317)
Treatment Group	2.007***	0.892***
	(0.207)	(0.236)
Diff in Diff	10.347***	0.232
	(0.355)	(0.377)
Observations	10,329	10,329
R^2	0.258	0.002

Table B.16: Triple DID (West 2017 Closure): The treatment group is defined as single permitted vessels. The control group is defined as dual permitted vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Year	2.065***	−1.149***
	(0.183)	(0.208)
Closure Days	3.520***	−0.161
	(0.130)	(0.184)
Treatment Group	−1.319***	−1.154***
	(0.040)	(0.050)
Triple Diff in Diff	9.906***	0.151
	(0.379)	(0.421)
Observations	460,195	460,195
R^2	0.056	0.002

B.2 Eastern Closures

IATTC closures are hypothesized to have a minimal to negligible effect on Hawaii's longline fishery. Typically, fishing effort centralizes near or within Hawaii's EEZ for two reasons. First, there is a positive relationship between trip cost and trip length. Second, once the initial catch is made, each vessel must operate on a fixed time budget to land their catch while it is still fresh. Eastern waters are not as populated with Hawaii longline vessels relative to western waters thus impacts of an eastern closure should be minimal. We present results from the four remaining eastern closures in Sections B.2.1, B.2.2, and B.2.3, B.2.4.

Contrary to our initial hypothesis, we estimate a negative to negligible effect on catch during an eastern closure relative to non-closure years, refer to Tables (B.18), (B.22), and (B.26). As the eastern closures become more expected, vessels seem to slowly adapt. By 2016, Sngl/<24 vessels drop their hooks more west relative to all other non-closure years and catch increases, shown in Tables (B.29) and (B.30). By 2017, we see a positive western movement amongst all fishery subgroups leading to an increase in catch for the entire fishery relative to non-closure month-day combinations, refer to Tables (2.5) in the main text.

Defining our treatment group to be large vessels we show a negative effect on catch for the initial eastern closures. For the eastern 2016 and 2017 estimates on catch vary across identification strategies. The Within-Year DID indicate catch was higher for the larger vessels than for the smaller, during the 2015 closure. Both identification strategies estimate catch to be higher for the treated group during the 2017 closure.

B.2.1 East 2013

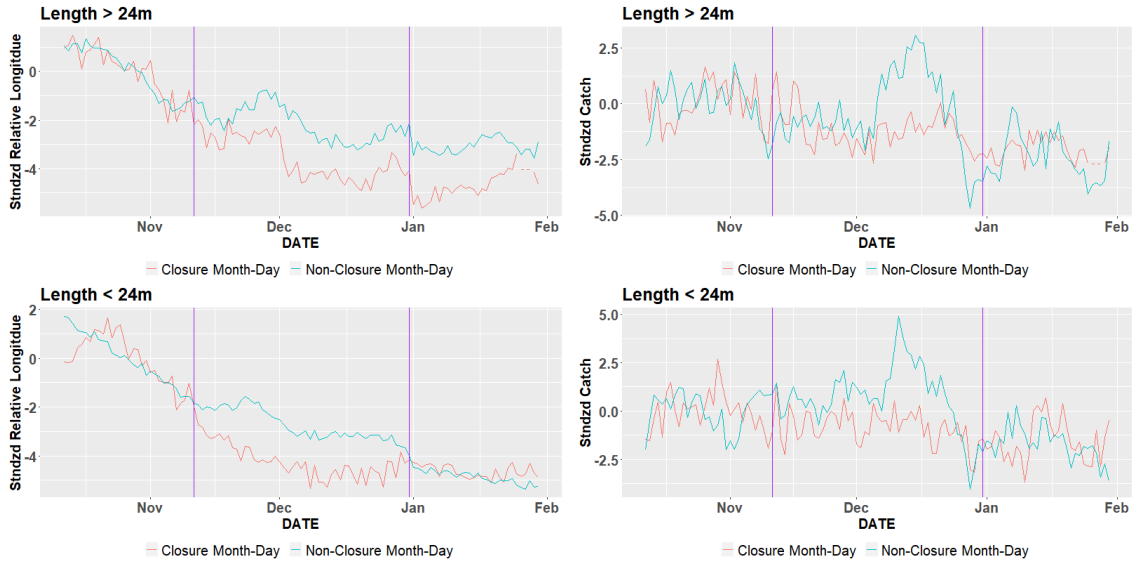

Figure B.5: Comparing Fishing Conditions for the 2013 Eastern Closure: All time series include fishing activities 30 days pre and 30 days post closure start and end respectively. Left panel represents longitude relative to HNL port and the right panel represents catch.

Table B.17: Temporal DID (East 2013 Closure) Longitude Relative to HNL: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	−0.446*	1.691***	1.454***	2.399***
	(0.238)	(0.496)	(0.102)	(0.219)
Closure Month−Day	−1.146***	−2.648***	−0.066*	−0.403***
	(0.112)	(0.341)	(0.039)	(0.092)
Diff in Diff	1.222***	−1.001	−3.443***	−2.824***
	(0.342)	(0.631)	(0.141)	(0.277)
Observations	10,248	2,313	100,059	23,881
R^2	0.009	0.034	0.008	0.009

Table B.18: Temporal DID (East 2013 Closure) Catch: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	1.834***	0.093	1.207***	1.381***
	(0.431)	(0.894)	(0.137)	(0.305)
Closure Month−Day	0.485***	0.400	0.091*	0.138
	(0.186)	(0.463)	(0.049)	(0.112)
Diff in Diff	−2.041***	−1.229	−0.193	−0.990**
	(0.582)	(1.192)	(0.196)	(0.416)
Observations	10,248	2,313	100,059	23,881
R^2	0.003	0.001	0.002	0.001

Table B.19: Within-Year DID (East 2013 Closure): The treatment group is defined as larger than 24m vessels. The control group is defined as less than 24m vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Days	−3.026***	−0.307*
	(0.126)	(0.181)
Treatment Group	1.205***	0.669**
	(0.219)	(0.309)
Diff in Diff	−0.249	−0.551
	(0.276)	(0.420)
Observations	12,081	12,081
R^2	0.062	0.001

Table B.20: Triple DID (East 2013 Closure): The treatment group is defined as larger than 24m vessels. The control group is defined as less than 24m vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Year	0.659^{***}	1.799^{***}
	(0.092)	(0.129)
Closure Days	-0.728^{***}	0.585^{***}
	(0.032)	(0.039)
Treatment Group	0.408^{***}	0.702^{***}
	(0.031)	(0.037)
Triple Diff in Diff	0.565^{**}	-0.569
	(0.288)	(0.431)
Observations	432,816	432,816
R^2	0.004	0.003

B.2.2 East 2014

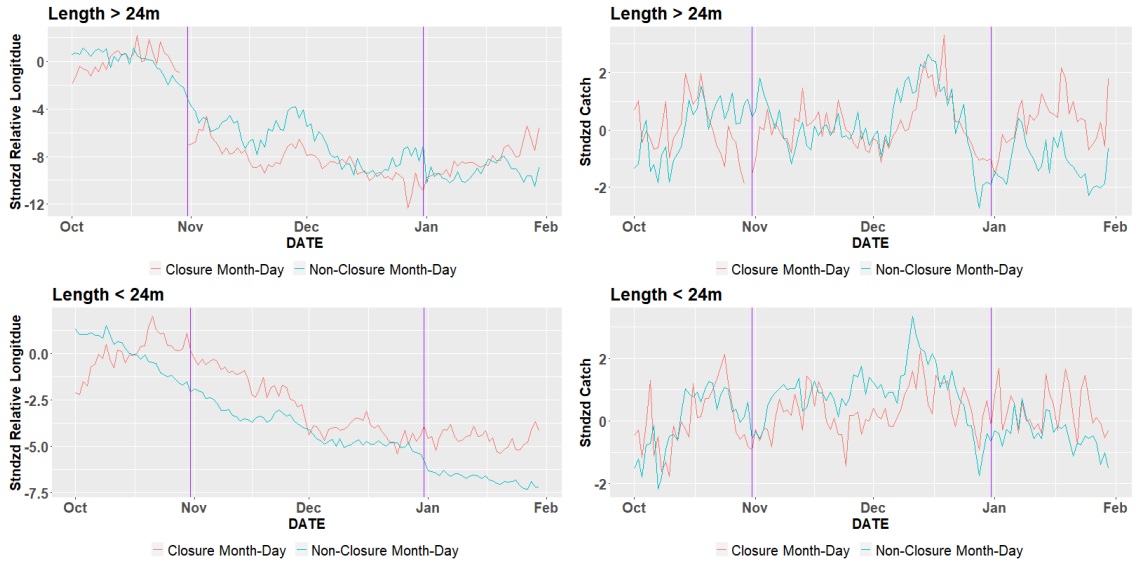

Figure B.6: Comparing Fishing Conditions for the 2014 Eastern Closure: All time series include fishing activities 30 days pre and 30 days post closure start and end respectively. Left panel represents longitude relative to HNL port and the right panel represents catch.

Table B.21: Temporal DID (East 2014 Closure) Longitude Relative to HNL: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	7.734***	4.398***	1.962***	2.578***
	(0.410)	(0.528)	(0.108)	(0.251)
Closure Month−Day	−0.211**	−1.879***	−0.083**	−0.762***
	(0.100)	(0.327)	(0.037)	(0.085)
Diff in Diff	−0.815	−4.168***	−0.475***	−4.491***
	(0.520)	(0.610)	(0.146)	(0.293)
Observations	10,995	2,500	110,436	26,932
R^2	0.140	0.034	0.007	0.018

Table B.22: Temporal DID (East 2014 Closure) Catch: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	1.143***	3.349**	2.199***	2.162***
	(0.438)	(1.646)	(0.164)	(0.340)
Closure Month−Day	0.368**	0.539	0.211***	0.297***
	(0.176)	(0.411)	(0.046)	(0.104)
Diff in Diff	−0.026	−2.898	−0.362*	−0.852**
	(0.632)	(1.911)	(0.215)	(0.430)
Observations	10,995	2,500	110,436	26,932
R^2	0.002	0.005	0.005	0.004

Table B.23: Within-Year DID (East 2014 Closure): The treatment group is defined as larger than 24m vessels. The control group is defined as less than 24m vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Days	−0.578***	−0.099
	(0.141)	(0.199)
Treatment Group	0.602**	0.866**
	(0.257)	(0.367)
Diff in Diff	−4.783***	−0.617
	(0.303)	(0.461)
Observations	12,998	12,998
R^2	0.044	0.001

Table B.24: Triple DID (East 2014 Closure): The treatment group is defined as larger than 24m vessels. The control group is defined as less than 24m vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Year	2.225***	2.466***
	(0.107)	(0.151)
Closure Days	−0.428***	0.583***
	(0.029)	(0.036)
Treatment Group	0.439***	0.694***
	(0.031)	(0.038)
Triple Diff in Diff	−3.983***	−0.639
	(0.312)	(0.469)
Observations	433,913	433,913
R^2	0.004	0.004

B.2.3 East 2015

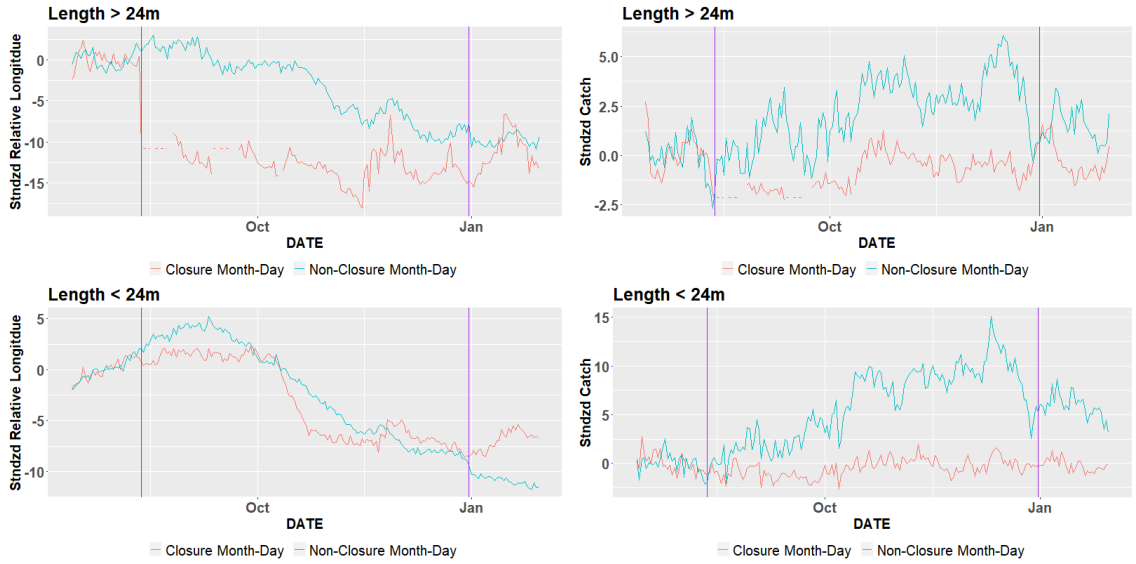

Figure B.7: Comparing Fishing Conditions for the 2015 Eastern Closure: All time series include fishing activities 30 days pre and 30 days post closure start and end respectively. Left panel represents longitude relative to HNL port and the right panel represents catch.

Table B.25: Temporal DID (East 2015 Closure) Longitude Relative to HNL: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	4.788***	1.312**	5.142***	6.293***
	(0.341)	(0.553)	(0.127)	(0.260)
Closure Month−Day	1.643***	−0.220	1.811***	2.125***
	(0.106)	(0.311)	(0.034)	(0.073)
Diff in Diff	−4.515***	−5.604***	−0.543***	−9.908***
	(0.401)	(0.595)	(0.154)	(0.304)
Observations	17,574	4,370	178,793	44,491
R^2	0.023	0.062	0.051	0.033

Table B.26: Temporal DID (East 2015 Closure) Catch: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	1.460***	1.171	2.073***	2.011***
	(0.464)	(0.718)	(0.158)	(0.352)
Closure Month−Day	0.402***	0.231	0.148***	0.370***
	(0.154)	(0.387)	(0.042)	(0.100)
Diff in Diff	−0.890*	−1.152	−0.909***	−1.261***
	(0.528)	(0.811)	(0.181)	(0.419)
Observations	17,574	4,370	178,793	44,491
R^2	0.001	0.001	0.003	0.001

Table B.27: Within-Year DID (East 2015 Closure): The treatment group is defined as larger than 24m vessels. The control group is defined as less than 24m vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Days	0.738***	−0.720***
	(0.140)	(0.167)
Treatment Group	0.904***	0.596*
	(0.253)	(0.336)
Diff in Diff	−7.930***	0.015
	(0.287)	(0.391)
Observations	20,060	20,060
R^2	0.070	0.002

Table B.28: Triple DID (East 2015 Closure): The treatment group is defined as larger than 24m vessels. The control group is defined as less than 24m vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Year	5.882***	2.190***
	(0.117)	(0.147)
Closure Days	2.561***	0.326***
	(0.024)	(0.028)
Treatment Group	0.232***	0.634***
	(0.036)	(0.042)
Triple Diff in Diff	−8.047***	−0.140
	(0.293)	(0.397)
Observations	441,042	441,042
R^2	0.053	0.003

B.2.4 East 2016

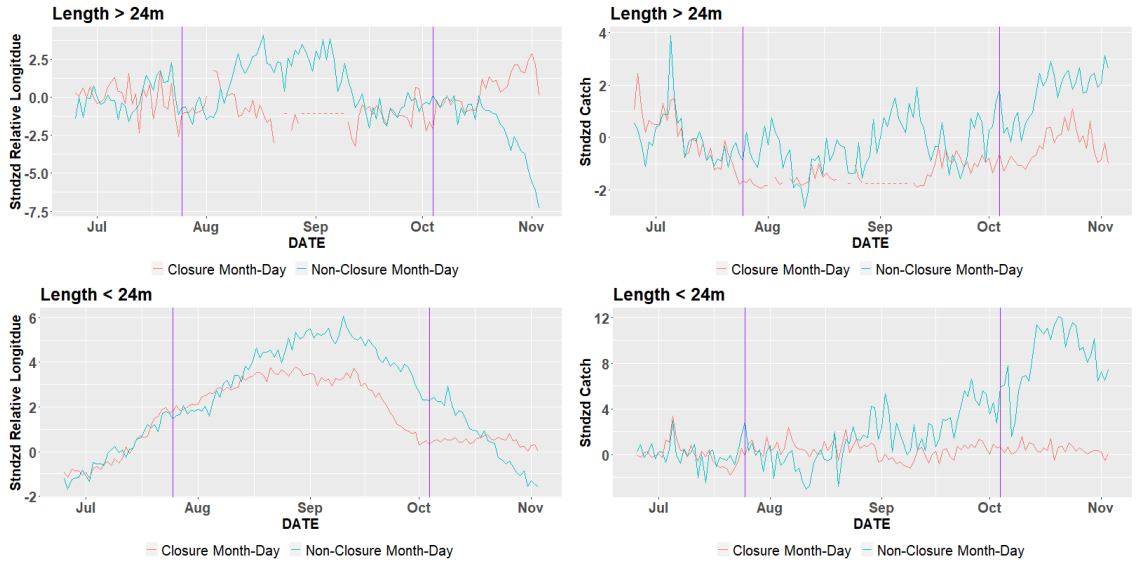

Figure B.8: Comparing Fishing Conditions for the 2017 Eastern Closure: All time series include fishing activities 30 days pre and 30 days post closure start and end respectively. Left panel represents longitude relative to HNL port and the right panel represents catch.

Table B.29: Temporal DID (East 2016 Closure) Longitude Relative to HNL: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	0.818***	−0.734	2.112***	0.412**
	(0.240)	(0.559)	(0.115)	(0.189)
Closure Month−Day	1.797***	0.276	1.156***	1.279***
	(0.140)	(0.338)	(0.041)	(0.083)
Diff in Diff	−1.174***	−4.218***	7.674***	−2.739***
	(0.361)	(0.675)	(0.145)	(0.303)
Observations	10,799	2,355	113,849	30,787
R^2	0.016	0.051	0.092	0.009

Table B.30: Temporal DID (East 2016 Closure) Catch: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	0.007	1.636**	0.889***	0.449
	(0.399)	(0.778)	(0.162)	(0.308)
Closure Month−Day	0.070	0.006	−0.282***	−0.116
	(0.206)	(0.493)	(0.052)	(0.121)
Diff in Diff	−0.942*	−3.677***	0.842***	−1.858***
	(0.499)	(0.928)	(0.219)	(0.457)
Observations	10,799	2,355	113,849	30,787
R^2	0.001	0.010	0.002	0.0004

Table B.31: Within-Year DID (East 2016 Closure): The treatment group is defined as larger than 24m vessels. The control group is defined as less than 24m vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Days	7.652***	0.358*
	(0.135)	(0.194)
Treatment Group	−0.533**	0.809**
	(0.214)	(0.318)
Diff in Diff	−9.706***	−2.655***
	(0.298)	(0.426)
Observations	12,316	12,316
R^2	0.267	0.003

Table B.32: Triple DID (East 2016 Closure): The treatment group is defined as larger than 24m vessels. The control group is defined as less than 24m vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Year	4.926***	0.781***
	(0.102)	(0.146)
Closure Days	4.158***	−0.298***
	(0.031)	(0.038)
Treatment Group	0.144***	0.653***
	(0.031)	(0.037)
Triple Diff in Diff	−10.169***	−2.895***
	(0.306)	(0.437)
Observations	433,359	433,359
R^2	0.091	0.002

B.3 Effective Closures

In our sample, there has only been three instances of an effective closure. The first occurred during 2015 and was previously presented in the main text. The second and third occurred in 2016 and 2017 and results for these closures are presented in Sections B.3.1 and B.3.2.

Catch amongst Sngl/<24 vessels during the 2016 closure increased relative to catch during the same time in all other non-closure years, refer to Table (B.34). With the exception of the 2016 outlier, effects of an effective closure appear to be negative to negligible across all other groups in all other closure years, refer to Table (B.38). Location of fishing effort appear to be mixed, refer to Tables (B.33) and (B.37). Larger (>24m) single permitted vessels are the portion of the fishery that is consistently hurt the most by an effective closure.

These results for larger vessels are magnified in our Within-Year DID and Triple DID models. Catch is statistically significantly lower for the Sngl/>24 vessels relative to all other vessels, highlighting the disproportionate distribution of opportunity across the fishery.

B.3.1 Effective 2016

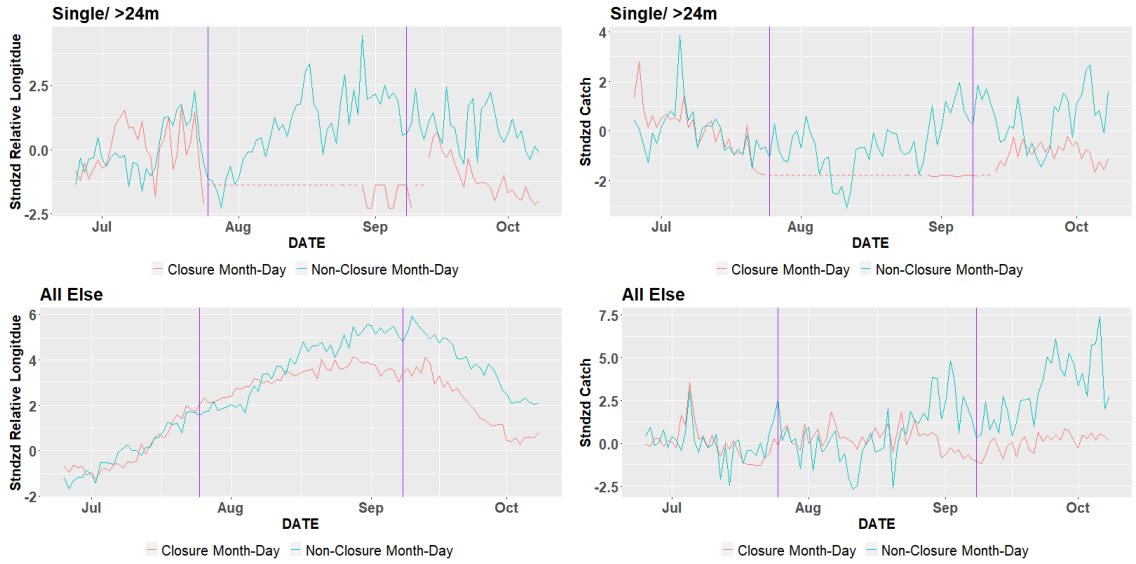

Figure B.9: Comparing Fishing Conditions for the 2016 Effective Closure: All time series include fishing activities 30 days pre and 30 days post closure start and end respectively. Left panel represents longitude relative to HNL port and the right panel represents catch.

Table B.33: Temporal DID (Effective 2016 Closure) Longitude Relative to HNL: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	−1.346***	−5.783***	4.025***	−0.349*
	(0.287)	(0.673)	(0.131)	(0.184)
Closure Month−Day	0.678***	−0.949**	0.860***	0.873***
	(0.162)	(0.371)	(0.049)	(0.095)
Diff in Diff	1.957***	1.526**	7.040***	−3.071***
	(0.444)	(0.775)	(0.155)	(0.783)
Observations	8,565	1,894	90,112	24,429
R^2	0.007	0.088	0.090	0.005

Table B.34: Temporal DID (Effective 2016 Closure) Catch: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	−0.731*	0.732	1.160***	0.313
	(0.382)	(0.892)	(0.167)	(0.324)
Closure Month−Day	−0.064	−0.038	−0.216***	−0.256*
	(0.238)	(0.549)	(0.060)	(0.140)
Diff in Diff	0.048	−2.486**	0.847***	−4.108***
	(0.545)	(1.060)	(0.260)	(0.541)
Observations	8,565	1,894	90,112	24,429
R^2	0.001	0.005	0.002	0.001

Table B.35: Within-Year DID (Effective 2016 Closure): The treatment group is defined as single permitted, larger than 24m vessels. The control group is defined as all other vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Days	6.482***	0.318
	(0.156)	(0.220)
Treatment Group	−3.098***	0.114
	(0.209)	(0.344)
Diff in Diff	−8.529***	−4.521***
	(0.893)	(0.609)
Observations	9,538	9,538
R^2	0.199	0.002

Table B.36: Triple DID (Effective 2016 Closure): The treatment group is defined as single permitted, larger than 24m vessels. The control group is defined as all other vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Year	6.198^{***}	0.685^{***}
	(0.118)	(0.148)
Closure Days	3.901^{***}	-0.534^{***}
	(0.037)	(0.045)
Treatment Group	-0.350^{***}	0.463^{***}
	(0.029)	(0.035)
Triple Diff in Diff	-9.295^{***}	-4.815^{***}
	(0.897)	(0.621)
Observations	464,965	464,965
R^2	0.063	0.001

B.3.2 Effective 2017

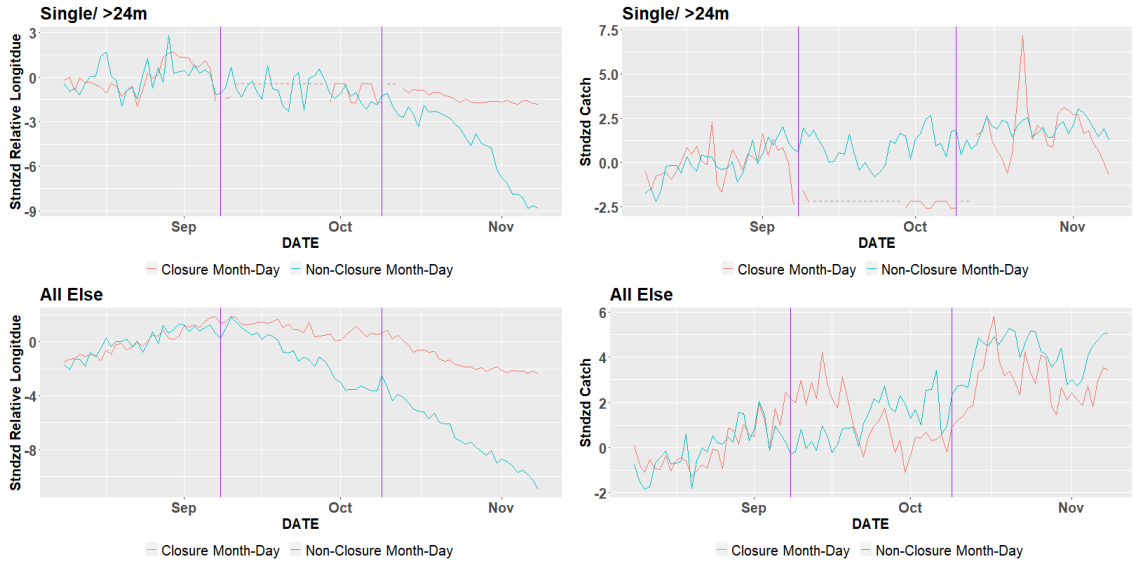

Figure B.10: Comparing Fishing Condtions for the 2017 Effective Closure: All time series include fishing activities 30 days pre and 30 days post closure start and end respectively. Left panel represents longitude relative to HNL port and the right panel represents catch.

Table B.37: Temporal DID (Effective 2017 Closure) Longitude Relative to HNL: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	−0.332	−1.294***	3.703***	1.317***
	(0.253)	(0.348)	(0.117)	(0.262)
Closure Month−Day	1.157***	0.633	0.810***	0.693***
	(0.172)	(0.423)	(0.051)	(0.098)
Diff in Diff	−2.726***	−4.942***	5.939***	−1.029
	(0.532)	(0.586)	(0.159)	(0.925)
Observations	8,161	2,088	84,636	22,362
R^2	0.011	0.079	0.070	0.003

Table B.38: Temporal DID (Effective 2017 Closure) Catch: The treatment group is defined within closure year, control groups are defined in all other non-closure years. Each column represents each of the four fishery subgroups. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Dual <24	Dual >24	Single <24	Single >24
	(1)	(2)	(3)	(4)
Closure Year	−1.288***	−1.477***	1.268***	0.334
	(0.295)	(0.467)	(0.142)	(0.305)
Closure Month−Day	−0.299	−0.939	−0.104	−0.114
	(0.241)	(0.590)	(0.063)	(0.140)
Diff in Diff	0.789	0.322	0.308	−3.503***
	(0.514)	(0.774)	(0.243)	(0.634)
Observations	8,161	2,088	84,636	22,362
R^2	0.002	0.007	0.002	0.001

Table B.39: Within-Year DID (Effective 2017 Closure): The treatment group is defined as single permitted, larger than 24m vessels. The control group is defined as all other vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Days	4.492***	0.147
	(0.175)	(0.197)
Treatment Group	−1.489***	0.156
	(0.274)	(0.315)
Diff in Diff	−4.267***	−3.481***
	(1.032)	(0.705)
Observations	9,585	9,585
R^2	0.077	0.001

Table B.40: Triple DID (Effective 2017 Closure): The treatment group is defined as single permitted, larger than 24m vessels. The control group is defined as all other vessels. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	Longitude from HNL	Catch
	(1)	(2)
Closure Year	5.699^{***}	0.871^{***}
	(0.100)	(0.118)
Closure Days	3.631^{***}	-0.171^{***}
	(0.042)	(0.052)
Treatment Group	-0.267^{***}	0.469^{***}
	(0.029)	(0.035)
Triple Diff in Diff	-4.491^{***}	-3.761^{***}
	(1.036)	(0.716)
Observations	464,081	464,081
R^2	0.040	0.001

Appendix C

Chapter Three Appendix

C.1 Additional 2015 Closure Specifications

When a closure is announced, captains are given a two-week grace period to land any bigeye that was retained before the closure commenced. Given that the hurricanes emerged during the beginning of a closure, one can argue that a flood of market quantity is caused by vessels returning to port before the grace period expires. In the main text we control for all closure days. In this appendix section, we isolate the effects of the grace period by only controlling for the first 14 days for both the western and eastern closure. *Western First 14 Indicator* takes a value of one if day t falls within the first two weeks of a western closure. Likewise, *Eastern First 14 Indicator* takes a value of one if day t falls within the first two weeks of an eastern closure. First and second stage results are given in Tables (C.1) and (C.2) respectively.

Results remain consistent with previous specifications. We find strong correlation between the instrument and the endogenous variable in the BIV model and weak correlation in our 3IV and 14IV models. Direction and magnitude are consistent in the second stage results. All specifications imply a more inelastic demand compared to that of OLS.

Table C.1: First Stage (14 day - Closures): Western First 14 Indicator flags the first 14 days after a western closure is announced. Eastern First 14 Indicator flags the first 14 days after an eastern closure is announced. Column (1) represents the first stage BIV, Column (2) the first stage 3IV, and Column (3) the first stage 14IV. Month fixed effects are used across all specifications. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	(1) Model BIV	(2) Model 3IV	(3) Model 14IV
Hurricane Indicator (Binary)	-0.314***		
	(-20.40)		
Western First 14 Indicator	0.152***	0.174***	0.243***
	(12.21)	(13.55)	(18.71)
Easterm First 14 Indicator	0.354***	0.310***	0.178***
	(25.84)	(20.60)	(11.36)
KILO		-0.0313	
		(-1.10)	
IGNACIO		-0.159***	
		(-6.02)	
JIMENA		-0.408***	
		(-11.38)	
day_03			0.649***
			(17.32)
day_07			-0.960***
			(-17.96)
day_12			-0.633***
			(-14.01)
Observations	195679	195679	195679
Month FE	1	1	1

Table C.2: Second Stage (14 day - Closures): Western First 14 Indicator flags the first 14 days after a western closure is announced. Eastern First 14 Indicator flags the first 14 days after an eastern closure is announced. Column (1) represents the standard OLS, Column (2) first stage BIV, Column (3) the first stage 3IV, and Column (4) the first stage 14IV. Month fixed effects are used across all specifications. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	(1) OLS	(2) Model BIV	(3) Model 3IV	(4) Model 14IV
Log Market Quantity (10K LBS)	-0.00551***	-1.386***	-0.740***	-0.248***
	(-2.97)	(-17.58)	(-24.45)	(-44.19)
Western First 14 Indicator	-0.166***	0.141***	-0.00538	-0.116***
	(-16.83)	(5.41)	(-0.46)	(-14.81)
Easterm First 14 Indicator	0.256***	0.577***	0.432***	0.323***
	(25.24)	(21.37)	(37.64)	(42.88)
Observations	195679	195679	195679	195679
First stage F		416.0	248.6	4772.8
J-Stat			3.44e-56	0
Month FE	1	1	1	1

C.2 Extending the Sample Size

Sampling bias can arise if there are some unobserved factors that affected market conditions in 2015 differently than all other years. Because we compare price differences within the same year, this should not affect our results. Nonetheless, we extend our sample size to include transactions one year prior and one year post 2015. Results are summarized in Tables (C.3) and (C.4). With an extended sample size, our results consistently estimate a more inelastic demand compared to OLS.

Table C.3: First Stage (Sample Size Extended): Column (1) the BIV model. Column (2) is our 3IV model. Column (3) is our 14IV model. Month fixed effects are used across all specifications. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	(1) Model BIV	(2) Model 3IV	(3) Model 14IV
Hurricane Indicator (Binary)	-0.224***		
	(-19.41)		
KILO		0.184***	
		(9.16)	
IGNACIO		-0.178***	
		(-8.25)	
JIMENA		-0.623***	
		(-22.46)	
day_03			0.722***
			(25.74)
day_07			-1.065***
			(-24.27)
day_12			-0.656***
			(-17.66)
Observations	569106	569106	569106
Month FE	1	1	1

Table C.4: Second Stage (Sample Size Extended): Column (1) represents the standard OLS model that does not control for endogeniety. Column (2) is our BIV model. Column (3) is our 3IV model. Column (4) is our 14IV model. Month fixed effects are used across all specifications. *p<0.1; **p<0.05; ***p<0.01 for two-sided t test of statistical significance using heteroskedasticity-robust standard errors.

	(1) OLS	(2) Model BIV	(3) Model 3IV	(4) Model 14IV
Log Market Quantity (10K LBS)	-0.0169***	-2.150***	-0.621***	-0.221***
	(-12.51)	(-17.65)	(-23.10)	(-40.05)
Observations	569105	569105	569105	569105
First stage F		376.7	267.5	47343.7
J-Stat			2.22e-203	0
Month FE	1	1	1	1