# sFISHERIES CONNECTIVITY AND THE EFFECTS OF MANAGEMENT ON THE TOPOLOGY OF A MARINE SOCIO-ECOLOGICAL SYSTEM

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# ABSTRACT

# INTRODUCTION

Ecosystem based fisheries management (EBFM) focuses on interactions between species and on the ecological effects of the biophysical environment (REF). Due to a focus on these interactions, EBFM is often described as managing an ecosystem as a whole, rather than individual species. This approach recognizes that the food-web, abiotic conditions, and human harvest are all drivers of system dynamics and seeks to manage them holistically. As such, much work on EBFM has focused on building models of food-web dynamics, and to account for how abiotic conditions may drive species interactions. Interest in EBFM also comes at a time when the importance of human behavior is being recognized, natural-resource management and conservation efforts are increasingly framing approaches in terms of ecosystem services and characterizing ecosystems more broadly as social-ecological systems (SESs; Millennium Ecosystem Assessment 2005, Carl Folke's papers?). EBFM dovetails with these trends and advises managers that human impacts should be included both to better represent the ecological impacts fisheries have and to capture livelihoods and human well-being derived from harvest (Levin et al. 2009).

These efforts to model both social and ecological dynamics of commercial fishery systems represent progress. However, in general there has been a bias towards studying ecological dynamics, with less focus on social or economic interactions. This is especially true of fishing fleets, which are largely modeled as independent populations of specialist vessels with no exchange among fisheries. Yet just as generalist predators can couple disparate food chains through broad diet preferences (Baskerville et al. 2011), there is evidence that vessels are often generalists: strategically entering and exiting fisheries depending on short term fluctuations in market, regulatory and ecological conditions (Hentati-Sundberg et al. 2014; Kasperski and Holland 2013; Sethi, Reimer, and Knapp 2014); and that multiple fleets target the same species (Coleman et al. 2004). Ignoring these details is problematic because (1) how vessels respond to changes in management is a major source of uncertainty in fisheries science (Fulton et al. 2010) and (2) because an often stated management goal is precisely to map the flows of ecosystem services and to incorporate “human dimensions” (Mace 2014; Levin et al. 2009). Therefore, quantifying and understanding “fisheries connectivity” is important if we are to transform ecosystem-based fisheries management from a concept that is biased towards understanding food-web connectivity only, into a more holistic systems-based fisheries management, where the interactions within and between both social and ecological subcomponents are understood and quantified.

Here, we have developed a novel classification to: (i) calculate vessel-level participation in individual fisheries, (ii) determine emergent diversification of a vessel’s revenue and participation across fisheries, and (iii) describe networks of fisheries participation for entire communities (ports). We found that the majority of vessels examined were generalists, defined as those participating in, and receiving most of their revenue from more than one commercial fishery. In addition, the interconnectedness of fisheries participation varied strongly across ports. Previous work examining the participation of vessels across fisheries has shown that management can act as a driver of fishing specialization (Hentati-Sundberg et al. 2014; Kasperski and Holland 2013). So last, we also used these individual and community-level measures of fisheries diversification to evaluate how the introduction of the Pacific Trawl Rationalization (catch share) program in the federal groundfish fishery in 2011 influenced vessel-level participation in the fishery. A catch shares system gives each fisher an individual and tradeable quota, and it has been shown that they make fisheries more “efficient”, that is poor performing fishermen generally sell their quota to more successful fishermen. In the long run though, there is evidence to suggest that catch shares can lead to diminished participation in a fishery (REF). Here, we examine not only how many fishermen exit the groundfish fishery after the implementation of catch shares in 2011, but we follow where vessels go, in terms of what fisheries they participate in after the change. This detailed study of fishery connectivity highlights that heterogeneous and dynamic nature of the social component of marine systems. Incorporating such detail into existing conceptual and mathematical frameworks will enhance our ability to design and predict the consequences of natural management.

# METHODS

## Description of Data Sources

We collected vessel landings tickets for all commercial landings on the US west-coast between 2009-2013 from the Pacific Fisheries Information Network (PacFIN) database ([www.psmfc.org](http://www.psmfc.org/)). These data were filtered for vessels with an average of at least $5,000 in annual revenue and we further removed vessels that landed commercial catch in Alaska. We also did not analyze landings from 2011, a management transition year in which catch shares were established. In doing so we restricted our analysis to fisheries landings before and after the implantation of catch shares. We also removed landings from vessels that participated in the California Halibut trawl fishery due to concerns about inconsistencies in landing tickets (REF?). This left 2,413 vessels that were responsible for approximately 93% of the total revenue and biomass commercially landed on the US west-coast during this period.

## Defining Realized Fisheries

Fisheries are defined as harvest assemblages caught with a specific gear (van Putten et al. 2012; Boonstra and Hentati Sundberg 2014). The Pacific Fisheries Management Council (PFMC) has developed a set of sector-based definitions similar to this approach for the federally managed groundfish landings (www.pcouncil.org), but no equivalent exists for non-groundfish fisheries (Northwest Fisheries Science Center 2015). In order to treat the landings dataset uniformly, we applied a métier analysis to this landing data (Deporte et al. 2012) to build a set of realized fisheries. A métier analysis identifies realized fisheries by clustering the species composition of landings. This methodology requires choices in the way similarity among trips are measured, a clustering algorithm for grouping similar trips together, and a constraint that the methods can scale across hundreds of thousands of landings. In the following we specify our rational for these choices.

For our distance metric we used the Hellinger distance *D* (P. Legendre and Legendre 2012) to calculate the similarity in revenue profiles between trips and generated a pairwise distance matrix. This distance metric has the benefit that it is asymmetric, where the presence of a species in both trips is considered more informative than the absence of a species. The Hellinger distance between the species composition of two fishing trips *A* and *B* is defined as

|  |  |
| --- | --- |
|  | (1) |

where *ai* is the fraction of revenue derived from species *i* on trip *A*, *bi* is the fraction of revenue derived from species *i* on trip *B*, and *S* indicates the total number of species collected in both trips. With this metric, trips *A* and *B* become increasingly similar (and the Hellinger distance declines) as the proportion of revenue attributable to each of the *S* species becomes increasingly matched.

We identified realized fisheries as groups of trips with similar target assemblages using the infoMap community detection algorithm (Rosvall and Bergstrom 2008). This algorithm examines networks for subgraphs more interconnected to one another than the network in which it is embedded. To generate the required network we transformed the distance matrix into a similarity matrix by subtracting the distance metric’s upper limit (i.e. ) from each pairwise distance. The result is a weighted, undirected network where trips are connected by edges proportional to their similarity. However, because our dataset contained 340,466 unique trips, it was computationally intractable for us to perform clustering using a single matrix containing all pairwise similarities. To obtain manageable matrix sizes we used one year of landings (2010) which we split by gear. Pairwise distances among trips and community detection were calculated within each gear partition, which grouped trips into target assemblage categories. To classify the 2009, 2012 and 2013 trips to fisheries, we assigned each unclassified trip to the same realized fishery as the 2010 trip to which it was closest in multi-dimensional space using a k-nearest neighbors algorithm.

A challenge in testing the effectiveness of this classification method, and part of the reason for its need, is that there is not an independent classification of US west coast fisheries that we could use to compare the results. To address this issue, we tested the reliability of our classification approach by evaluating the extent to which it identified known spatial and temporal structure of well-described US west coast fisheries and fishery sectors. Specifically, because we did not bound our clusters spatially, temporally, or by vessel characteristics, we were able to compare our emergent realized fisheries to existing sector definitions of groundfish, and groundfish impacting fisheries provided by the Northwest Fisheries Science Center Observer Program (Northwest Fisheries Science Center 2015).

## Calculating Changes in Vessel and Community Level Fishing Diversity

Vessel revenue diversity is calculated using the effective Shannon index *H* (Jost 2006). This metric quantifies variability in the proportion of revenue *pf* derived from each realized fishery *f* (identified from the clustering approach described above), such that revenue diversity *H* for vessel *j* is calculated as

where *F* is the number of realized fisheries. We define specialist vessels as those that land in a single realized fishery (*H* = 1) and generalist vessels are vessels that land in more than realized fishery (*H* > 1).

To represent connectivity among realized fisheries at the port level we built directed, weighted networks where nodes represented a realized fishery, and the strength of the connections between nodes represented the number of vessels that landed catch in both over a given period. More formally, for each port *k* we built a network *Gk,X🡪Y* in which an edge weight between two nodes *X* and *Y* was the number of vessels participating in fishery *X* and *Y* divided by the total number of vessels that participated in fishery *X*. Similarly, is the number of vessels participating in both fisheries divided by the total number of vessels that participated in fishery *Y* (Fig. 1)*.*

To measure port-level fisheries connectivity we calculated the link density (*LD,* number of edges divided by nodes) which scales both with network size and interconnectedness. Because the network is directed, this value can be interpreted as the two times the average number of fisheries to which a fishery is connected (i.e. all vessels participate in both fisheries) at port *k*.

In order to test whether realized fishery participation at the vessel or port level changes as a function of the implementation of catch shares, we assigned vessels and ports to one of three categories: *M1*, *M2* or*M3*. *M1*: vessels/ports unaffected by catch shares were termed the *general participants*, which included only those vessels/ports for which we observed no commercial landings in the catch-shares affected fishery in 2009-2010 or 2012-2013 (*nvessels* = 1,878, *nports* = 52). *M1*: *catch share participants* were those vessels/ports had landings in the limited entry trawl fishery prior to 2011 and continued to have catch share quota landings after 2011 (*nvessels* = 71, *nports* = 16). *M3*:, *limited entry exits* were those vessels/ports that landed in the limited entry trawl fishery prior to 2011, but had no landings using catch shares quota after 2011 (*M3, nvessels =* 35, *nports* = 10, Fig. 2). By comparing the general participants to vessels/ports affected by catch shares (*catch share participants* and *limit entry exits*) we were able to control for exogenous inter-annual variation in revenue diversity present in both groups of vessels.

## Effects of Catch Shares on Revenue Diversity and Fisheries Connectivity

We used linear regressions to determine whether a change to catch shares management in the limited entry groundfish trawl sector was associated with a change in revenue diversity at the vessel level and/or a change in fisheries connectivity at the port level. For each vessel and port (henceforth we drop the indices for vessel and port for brevity)we calculated the change in revenue diversity as the difference in revenue diversity before (*Hpre*) and after (*Hpost*) the implementation of catch shares as *ΔH = Hpost – Hpre*. We defined a change in fisheries connectivity for each port as the difference in link density before (*Cpre*) and after (*Cpost*) the implementation of catch shares as *ΔC = Cpost – Cpre*. Thus a value of zero for Δ*H* or Δ*C* indicated there was no change in revenue diversity or fisheries connectivity for a given port, respectively, between the two periods, and a positive value indicated the vessel or port increased the evenness and/or the number of fisheries from which it received revenue.

At the vessel level, if catch shares allowed more flexibility in fisheries participation, we would expect that catch share participants would, on average, demonstrate increased revenue diversity after the implementation of catch shares. To this end, we conducted a linear regression to determine the relationship between Δ*H* and the three vessel categories *M1* (general participants), *M2* (catch share participants) and *M3* (limited entry exits). However, the ability to change diversity between two periods is related to the starting period diversity. For example, if a vessel is a specialist (i.e. *H* = 1), then it is impossible for that vessel to have a drop in diversity and any random variation will bias *ΔH* upwards. Similarly, if a vessel was maximally diversified, then the vessel could either remain the same or with a random drop in diversity. Thus, we also evaluated a model in which the pre-catch share revenue diversity *Hpre* of each vessel was a covariate.

At the port level, we used similar regressions to those employed at the vessel level, to determine whether a change to catch shares management in the limited entry groundfish trawl sector was associated with a change in fishery connectivity. Thus we also regressed Δ*C* against catch shares participation with and without *Cpre* to catch shares as a covariate.

In both the vessel and port level analyses, the Akaike Information Criterion (AIC) was used to find the most parsimonious model which balanced both the goodness of fit, as measured by likelihood, and model complexity, as measured by the number of parameters (Burnham and Anderson 2002). We calculated 95% confidence intervals by randomly selected data with replacement, from both the vessel and port datasets, and repeated this procedure 10,000 times.

# RESULTS

## Realized Fisheries of the US West-coast

Applied to the landing ticket data, our clustering algorithm identified 109 realized fisheries (Appendix, Table 1). Realized fisheries often consisted of a single species, but could also comprise assemblages of species (Fig. S1a). Whether their catch consisted of a single species or multiple species, the realized fisheries were characterized by distinct temporal and spatial structure (Fig. S2a, b). This structure showed strong agreement with the NWFSC Observer sector designations, as did comparisons of vessel sizes and catch composition (single- vs. multi-species, Table 1).

The realized fisheries also varied by several orders of magnitude in effort (number of trips) and revenue (Fig. S1b), with a small number of fisheries accounting for the majority of effort and revenue. For example, only 10 of the 109 fisheries were responsible for 90% of ex-vessel revenue and landings (pounds) in the time period we examined (Table 1). These key realized fisheries, listed as target assemblage-gear pairs are: Dungeness crab-crab pot, market squid-purse seine, albacore tuna troll, groundfish bottom trawl, pink shrimp-trawl, sablefish-long line, salmon-troll, sardine-purse seine, spiny lobster-pot, and red urchin-diving, and included sectors which have been well-studied, but not quantitatively described prior to now, for example the dungeness crab pot (Botsford and Wickham 1978), spiny lobster pot (Kay et al. 2012), and red urchin diving (Smith and Wilen 2003) (Table 1) realized fisheries.

## Changes in Vessel and Community Level Fishing Diversity

We found that between the start of 2009 and the end of 2010, 66% of commercial vessels on the west coast participated in more than one realized fishery (Fig. 2a) although the degree to which vessels diversified varied. Breaking these patterns down regionally using PFMC management regions, generalists outnumbered specialists (Fig. 2b). The distribution of diversity varied among the generalists, from vessels that were highly specialized, but had a few landings in additional fisheries to those that fished in many fisheries evenly (Fig. 2c). Notably, the majority of diversified vessels revenue was dominated by revenue from a single fishery (71%), with very small percentages coming from alternatives. However almost a quarter (24%) of diversified vessels were participating in at least two fisheries equally, with some vessels (4%) participating evenly in more than three fisheries (Fig. 2c).

The preceding analysis focused on fishing strategies employed by individual vessels, without consideration of how those strategies came together to create characteristic fisheries participation networks for specific ports. We found differences in the number and interconnectedness of fisheries across ports (Fig. 3). Ports had anywhere between 0-7 fisheries connected. This variation is exemplified by participation networks in Santa Barbara, CA, Eureka, CA, and Oakland, CA (Figs. 3a-c). Santa Barbara was characterized by a complex participation network, with more than double the average link density of Eureka (see Appendix for all port participation networks). Most ports had a spectrum of vessels landing at them and we found that there was a positive, albeit weak, relationship between vessel and port level diversity (Spearman’s correlation 0.185, p < 2.2e-16, Fig S3).

We found that the implementation of catch shares was associated with a minority (6%) of vessels leaving commercial fishing altogether while 66% of vessels continued to participate in the affected fishery. Of vessels which continued fishing in the catch-shares fishery, 87% of vessels adjusted their fishing participation, entering or exiting new fisheries. A third group consisted of vessels that exited catch shares but continued to fish commercially (28%) (Fig 4). These vessels showed a mixed response, with increased and decreased fishing diversity observed.

Over our study time period, vessels become more diversified on average (Fig 4). We found though that the change in revenue diversity was strongly explained by the revenue diversity the vessels had in 2009-2010. Vessels with higher participation diversity prior to catch shares were more likely to show a reduction in diversity following catch shares (Table S2). We also found that and a vessel’s participation in catch shares was related to changes in revenue diversity. Vessels that participated in catch shares, post 2011, saw an increase in their revenue diversity that was twice that for vessels which exited the catch share fishery. At the port level we found that ports decreased their fisheries connectivity on average, and this was strongly predicted by past link density (Table S1, S2). We found that the model which best explains the change in fisheries connectivity included only a term for previous fisheries connectivity (*Cpre*) and does not include terms for a port’s relationship to catch shares (*Mn*).

**DISCUSSION**

There is widespread recognition that ecosystem-based management requires an understanding of the connectivity within and between the human and ecological subcomponents of marine systems (Anderson et al. 2015). Mapping these social-ecological connections have resulted in considerable insight, often by identifying drivers unobservable from social or ecological studies alone (Brashares et al. 2004; Lade et al. 2015). This connectivity is particularly important in fisheries, where socioeconomic or ecological changes in one fishery often have cascading effects that ultimately influence others (Steneck et al. 2011; Lade et al. 2015). Yet despite this recognition, social dynamics are often missing and fishing fleets are usually represented as homogenous and static (Field 2004). Our results highlight that on the contrary fishing fleets are highly heterogeneous and continually changing in size, effort level, and composition, as numerous exogenous and endogenous forces influence them (Opaluch and Bockstael 1984). Specifically, for the US west-coast, we have found that the majority of vessels are generalists, and that a change in management is associated with a shift in patterns of participation across fisheries.

Changes in system characteristics, be it management, ecology or markets, have been previously shown to affect fishing participation. For example, Hentati-Sundberg et al. (2014) has shown how Swedish commercial fishermen have grown increasingly specialized as management became more restrictive and Steneck et al. (2011) document how Maine fishermen have increasingly become dependent on a single species due to interactions among markets and ecological conditions. Here, we found that along the whole the US west-coast, greater than 60% of commercial fishing vessels were generalists, participating in more than one realized fishery. The revenue of each of these generalists is thus tied to multiple fisheries, effectively connecting them and setting up the potential for linked social/economic dynamics and coupled ecological dynamics of target species. The social implications of generalist fishing practices have been most directly related to reduced exposure to income risk (Kasperski and Holland 2013; Sethi, Reimer, and Knapp 2014), with previous work identifying that vessels with increased revenue diversity have less variable revenues (Kasperski and Holland 2013). Further work is need to determine whether the ubiquity of generalists on the US west-coast is indicative of systemic risk-adverse behavior, and whether revenue diversity confers a general resilience in fishermen’s revenues to perturbation, such as diminished catch due to exogenous environmental factors, or a change in management of one particular fishery.

Furthermore, much of the previous research on fishery diversity and revenue variability (REFs) has primarily focused on the impacts of catch shares on the vessels that have continued to operate within the fishery of interest, assuming that vessels that exit also exit commercial fishing entirely. Our analysis shows that for the US west-coast, the majority of vessels that participated in the groundfish fishery prior to the implementation of catch shares, continued to operate after the management change albeit in other realized fisheries. This highlights the need to quantify how a management change, or any other perturbation, is felt throughout the marine social-ecological system as vessels/individuals reorganize their participation across realized fisheries.

The redistribution of fishing effort across a fisheries participation network is directly analogous to (changes in) predation pressure in a food-web. Specifically, if we think of vessels as predators, then the realized fisheries that they participate in are their prey. As we have shown, there are many specialist vessel/predators, but the majority of fishermen/vessels are generalist predators with a broad diet preference. In natural systems, a predator’s diet preference is largely determined by the physiological adaptations of the predator. Here, the analogy extends to the gear and skill that each vessel has. This is relevant when considering the redistribution of fishing effort across participation networks. Vessels geared and skilled at harvesting certain sets of species, will not immediately start harvesting other target species that require completely different gear and skills. This is reflected in the different realized fisheries that any one vessel participates in over a given year, and in general it is related to the topology of the participation networks. Here, we have used possibly the simplest network metric – link density – to describe the topology of the fisheries participation networks of the US west coast. However, there are many more network metrics that are relevant, many that again have direct analogies to food-webs. Two stand out: (1) measures of node centrality have been used to identify “keystone” species in food-webs, those that if removed from the food-web would lead to a disproportionately large impact on the whole system. Applied to the participation networks, measures of centrality would identify “keystone fisheries”, those that most vessels would participate in (and possibly gain most of their revenue from) at some point of the year. We have not shown results of centrality analyses here, but upon performing them we have identified several keystone fisheries along the US west-coast, such as Dungeness crab for several ports in Oregon. (2) The second network metric is modularity, which describes the presence of groups of well-connected realized fisheries. Network modularity is an important property of any complex system (Levin Refs), providing resilience to perturbation by isolating effects to subcomponents. Here, modules in the participation networks would identify groups of similar vessels, based on what they do on the water, that can be used to identify discrete management units.

These first order properties of the participation networks are key to quantifying how any perturbation – a management or environmental change – will effect the whole marine social-ecological system. However, there are second order properties of the participation networks that are worth considering too. In particular, not only are the links between realized fisheries heterogeneous, they are changing over time as fishers/vessels re-tool and learn new skills. Much like in ecology, evolution is continually selecting for new adaptations, albeit at a much slower rate than the ecological dynamics. Another key property is the transitivity of the participation networks. Transitivity describes multi-step connections, and these are particularly important when considering the connections between the fishery participation networks, and the food-web on which it sits. For example, if there is a pair of species that are unconnected ecologically (i.e. there is no link between them in the food-web), but there are vessels that harvest both (i.e. there is a link in the participation network between these species’ realized fisheries), then there is a transitive link. As a consequence, a management change that affects vessel participation in one fishery, will affect that status of the (ecologically unconnected) stock of the other species. Dungeness crab and albacore tuna fisheries on the US west coast provide an appealing (but currently untested) example. Here, we find these two realized fisheries to be commonly connected by vessels at the port level, yet these species do not interact directly in the ocean. Examining changes in revenue diversity and vessel participation in the albacore tuna fishery after the recent closure of the Dungeness crab fishery in Washington and Oregon would be an excellent test of how connectivity influences fisheries participation. In general, environmental or management perturbations will ripple through these participation networks, and that their topology as well as the adaptability of fishermen, will largely determine their economic impacts.

In conclusion, our results highlight the need to consider fisheries as connected and dynamic entities. Not only does EBFM need to acknowledge the links between species in food-webs, but there needs to be an equal emphasis on the connectivity between fisheries, based on the participation of vessels, and on the economic consequences of the topology of the participation networks. We have shown that fishery participation is heterogeneous, varying greatly from place to place, and dynamic, responding to the implementation of catch shares in the groundfish fishery. If we can broaden the conceptual and mathematical models of marine systems to include such properties, then we will be truly on our way to developing systems-based fisheries management, which is likely to lead to better performing governance institutions in the future.

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**TABLES**

**Table 1**. We summarize fleet characteristics for three realized fisheries and compare to the corresponding NWFSC Observer sector description. Parenthetical values represent the percentage of trips which fell within expected ranges. The following fisheries represent (with pink shrimp and limited entry groundfish) the top ten realized fisheries by revenue. Fleet characteristics for which no corresponding NWSFC observer sector is present are presented as 95 percentiles for length, latitude and seasonality.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Fishery**  Sector name if applicable | **Latitude**  decimal degrees | **Catch composition**  % trips multispecies | **Seasonality**  fishing season | **Vessel Length**  ± 1 ft |
| Limited entry groundfish trawl/catch shares | 35.4-49  (97.9%) | 100%  (98.2%) | year-round | 35-95  (99.5%) |
| Pink shrimp trawl | 35.8-49  (97.9%) | NA | Apr 1 – Oct 31  (99.8%) | 38-105  (100%) |
| California halibut trawl | 37.4 – 34.05  (96.5%) | CA halibut dominated | year-round | 29-71  (99.8%) |
| Dungeness crab pots | 36.8-47.6 | 0.9% | Oct 26 – Aug 8 | 22-67 |
| Market squid seine | 33.7-36.8 | 6.8% | May 24 – Feb 25 | 36-80 |
| Albacore troll | 37.5-46.9 | 0.6% | Jul 10-Oct 22 | 23-72.5 |
| Sablefish long-line | 33.2-48.4 | 70% | Jan 16-Dec 15 | 20-57 |
| Shore-side Hake | 43.3-46.9 | 92% | Jun 16-Nov 15 | 65-129 |
| Chinook salmon troll | 35.4-48.4 | 14% | Apr 11-Oct 22 | 20-50 |
| Sardine seine | 33.7-46.9 | 42% | Jan 8-Oct 22 | 45-80 |
| Spiny lobster pot | 32.7-34.4 | 8.3% | Oct 5-Mar 12 | 18-42 |

**FIGURE CAPTIONS**

**Figure 1**. Using landing tickets we used price per pound (*ppp*) and landed weight to calculate revenue per species per trip. We aggregated this landings to trips and grouped trips by gear. In each gear partition we identified realized fisheries by measuring pairwise similarity of each trip’s revenue composition of catch using the Hellinger distance, and clustered using infoMap. Using these fishery designations we mapped participation at the vessel level, quantifed revenue diveristy and fisheries connectivity at the port level.

**Figure 2**. Distribution of revenue diversity at the vessel level measured as the effective shannon index of revenue plotted in three different ways: A) coastwide, B) by management region, and C) breakdown of generalism for each management sector. We defined generalists as vessels that landed in more than one realized fishery. We found that generalists outnumbered specialists (A, B), although the degree of generalism varied (C).

**Figure 3**. Spectrum of fisheries connectivity present in fishing communities on the US west coast as illustrated by participation networks for A) Santa Barbara, CA; B) Eureka, CA; and C) Oakland, CA. Here nodes represent realized fisheries where edge width is proportional to the proportion of vessels that participate in the connected fisheries. Vertex size is proportional to the log number of vessels which participate in each realized fishery. Color of nodes is consistent across networks, reds represents pots, greens are hook and line, blues are nets, pinks are shrimp trawls, oranges are groundfish trawl, purples are miscellaneous and yellows are troll fisheries. D) Fisheries connectivity, measured as link-density for all ports on US west coast with more than three vessels landing between 2009-2010. Dark bars correspond to the network above them.

**Figure 4**. We map the ways that a vessel can respond to the implementation of catch shares. Vessels that were directly affected by catch share implementation are those that fished in the limited entry (LE) groundfish fleet between 2009-2010. After 2011, vessels either continue to participate in the groundfish trawl fishery by landing with quota, or leave the catch share fishery and either leave commercial fishing entirely or continue to fish in other commercial fisheries. The width of the bar in the decision tree is proportional to the absolute number of vessels which follow a given path given by the number. Percentages are relative to each decision point. We find that very few vessels which stopped fishing in the groundfish fishery actually left commercial fishing altogether, and vessels which participated in catch shares changing their participation across fisheries.

**Figure 5**. Estimated effects of catch shares on revenue diversity for vessels, bars represent 95% confidence intervals. Vessels that participate in catch share increase in revenue diversity more than either the general participants or those that exited catch shares. At the port level the best supported model does not include a term for participation in catch shares.