November 2017 ■ RFF WP 17-23

WORKING PAPER

Identifying the Potential for Cross-Fishery Spillovers: A Network Analysis of Alaskan Permitting Patterns

Ethan T. Addicott, Kailin Kroetz, Matthew Reimer, James N. Sanchirico, Daniel K. Lew, and Justine Huetteman

1616 P St. NW
Washington, DC 20036
202-328-5000 www.rff.org

RESOURCES FOR THE FUTURE

Identifying the Potential for Cross-Fishery Spillovers: A Network Analysis of Alaskan Permitting Patterns

Ethan T. Addicott, Kailin Kroetz, Matthew Reimer,
James N. Sanchirico, Daniel K. Lew, and Justine Huetteman

Abstract

Many fishermen own a portfolio of permits across multiple fisheries, creating an opportunity for fishing effort to adjust across fisheries and enabling impacts from a policy change in one fishery to spill over into other fisheries. In regions with a large and diverse number of permits and fisheries, joint-permitting can result in a complex system, making it difficult to understand the potential for cross-fishery substitution. In this study, we construct a network representation of permit ownership to characterize interconnectedness between Alaska commercial fisheries due to cross-fishery permitting. The Alaska fisheries network is highly connected, suggesting that most fisheries are vulnerable to cross-fishery spillovers from network shocks, such as changes to policies or fish stocks. We find that fisheries with similar geographic proximity are more likely to be a part of a highly connected cluster of susceptible fisheries. We use a case study to show that preexisting network statistics can be useful for identifying the potential scope of policy-induced spillovers. Our results demonstrate that network analysis can improve our understanding of the potential for policy-induced cross-fishery spillovers.

Key Words: Fishing portfolios, leakage, network theory, spillover effects, fishery policy

JEL Classification Numbers: Q22

Contents

Identifying the Potential for Cross-Fishery Spillovers: A Network Analysis of Alaskan Permitting Patterns

Ethan Addicott, Kailin Kroetz, Matthew Reimer,
James N. Sanchirico, Daniel K. Lew, and Justine Huetteman*

1. Introduction

Most commercial fishery policies are directed towards a single species in a particular region and caught by a certain gear, even though fishermen participate in multiple regions, catch multiple species, and use multiple gears. Policy assessments that fail to account for the richness of fishing enterprises can result in an incomplete understanding of the socioeconomic consequences of management changes in target and non-target fisheries, as well as in fishing communities. For example, fishermen may shift fishing effort to other fisheries in response to a policy change in the target fishery. This so-called "leakage" can result in both positive and/or negative spillover effects on both fishermen and communities involved in the impacted fisheries (e.g., Cunningham et al. 2016). Furthermore, participation linkages across fisheries are especially important to understand given recent work showing that a diversified portfolio of fisheries can help fishermen and communities mitigate risk and smooth incomes (Kasperski and Holland 2013, Sethi et al. 2014a, Anderson et al. 2017, Cline et al. 2017). The mismatch between the scope of past management policies and the reality of fisherman decision-making is an impetus for expanding our understanding of multi-fishery participation.

* Addicott: School of Forestry and Environmental Studies, Yale University, New Haven, CT 06460; email: ethan.addicott@yale.edu. Kroetz: Resources for the Future, Washington, DC 20036; email: kroetz@rff.org. Reimer: Institute of Social and Economic Research, Department of Economics and Public Policy, University of Alaska Anchorage, 3211 Providence Drive Anchorage, AK 99508; email: mreimer2@alaska.edu. Sanchirico: Resources for the Future, Washington, DC 20036; Department of Environmental Science and Policy, University of California, Davis, California 95616; email: jsanchirico@ucdavis.edu. Lew: AFSC, NMFS, NOAA; Department of Environmental Science and Policy, University of California, Davis, California 95616; email: dan.lew@noaa.gov. Huetteman: Resources for the Future, Washington, DC 20036; email: huetteman@rff.org.

Disclosure statement: The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

Acknowledgements: We thank Jacqueline Ho for research assistance. Funding for this research was provided by Resources for the Future and the North Pacific Fisheries Research Board (NPRB). The views and opinions expressed in this paper are the authors' own, and do not necessarily reflect those of Yale University, Resources for the Future, University of Alaska, the University of California, Davis, the National Oceanic and Atmospheric Administration, or the U.S. Department of Commerce.

The likelihood and degree of leakage from a single-fishery policy depends on the extent to which fishermen can substitute between the target fishery and other fisheries. Ex ante predictions of spillover impacts therefore require policy makers to identify fisheries that are susceptible to leakage from a proposed single-fishery management action. To do so, policy makers must first understand the prevailing patterns of cross-fishery participation. For instance, to what extent are permits for the target fishery held in common with permits for other fisheries? Are there fisheries that are more heavily connected to other fisheries through joint permitting, making them more likely to generate spillover effects into other fisheries? Are there fishery characteristics that make joint permitting and spillover impacts from a management change more likely?

In this paper, we investigate the degree of interconnectedness and characteristics of jointly permitted fisheries in the Alaska region to better understand the potential for single-fishery policy spillovers. Despite the extensive work on the benefits of diversification of individual and community fishing portfolios in Alaska (Kasperski and Holland 2013, Sethi et al. 2014a, Anderson et al. 2017, Cline et al. 2017), as well as analyses outside Alaska demonstrating that single-fishery management actions can spill over into other fisheries (Asche et al. 2007, Hutniczak 2014, Cunningham et al. 2016), there is limited information in Alaska on cross-fishery permitting patterns and the scope for potential spillover effects from single-fishery policies.

We use tools and methods derived from network theory to characterize fisheries interconnectedness in Alaska, and investigate how interconnectedness varies based on fishery characteristics, including the areal extent of the fishery (i.e., statewide versus regional) and management jurisdiction (i.e., federally-managed versus state-managed fisheries). As demonstrated by Fuller et al. (2017), a particular strength of network statistics is that they can capture fishery connectivity that extends beyond the first-degree, which allows us to examine the potential for spillover impacts to spread beyond those fisheries directly connected to the target fishery. We identify clusters of fisheries whose permits are more likely to be held in common with other fisheries in the same cluster, but less likely with fisheries outside the cluster. This allows us to examine the likely scope for potential spillover effects from single-fishery policies and to identify characteristics of fisheries that tend to have a relatively high degree of cross-fishery permitting. We consider several fishery characteristics that have either been shown or hypothesized to be associated with cross-fishery permitting: using the same gear (Radtke and Davis 2000), targeting the same or similar species (Radtke and Davis 2000, Cunningham et al. 2016), and/or geographic proximity (Sethi et al. 2014a). Finally, to examine the effectiveness of network methods for identifying the potential for spillover, we explore whether the network of fisheries connected to the Bristol Bay King crab pot (BBK) fishery prior to the implementation of the Individual Transferable Quota (ITQ) program in 2004 serves as a good proxy for changes that took place after ITQ introduction.

Our results demonstrate that network analysis can greatly contribute to our understanding of policy-induced cross-fishery spillovers. We find that the Alaska fisheries network is highly connected--all but one of the fisheries form a connected graph, with approximately one-third of all potential fishery pairs sharing at least one permit holder. Furthermore, we find that there is significant heterogeneity in interconnectedness across fisheries, suggesting there is variability in fisheries' likelihood of generating and being susceptible to network shocks, such as changes to policies or fish stocks. Fisheries that are federally managed and/or have a statewide geographic scope tend to be larger and more likely to be core fisheries in the network—i.e., they share permit holders with more fisheries, share a greater number of permit holders, and are more central to the network, on average. We find that fisheries that share similar geography—and to a lesser extent fishing gear—are more likely to be a part of a highly connected cluster of fisheries, suggesting that geographically similar fisheries may be a good place to look for potential spillover effects from a management change in one of Alaska's fisheries. Moreover, significant cross-fishery permitting exists between federal and state fisheries, highlighting the importance of considering potential impacts on state fisheries when designing and evaluating federal fishery management policy, and vice versa. Finally, our case study of the BBK fishery indicates that preexisting network statistics can be useful for identifying the potential scope of cross-fishery policy-induced spillovers.

2. Material and Methods

2.1. Alaska Fisheries

There exist a variety of state- and federally-managed commercial fisheries in the waters off Alaska, spanning multiple targeted species, gear types, locations, and management institutions. Commercial fisheries that occur within three nautical miles from shore are managed by the State of Alaska, while fisheries that occur greater than three nautical miles offshore are federally managed.[1] These Alaskan fisheries are prosecuted by both residents and non-residents,

[1] There exists a subset of fisheries that occur more than three nautical miles offshore within the U.S. exclusive economic zone for which management is delegated to the State (e.g., crab fisheries). For more detail on Alaska fisheries see Appendix.

using a variety of vessel types, ranging from small skiffs using longlines to catch Pacific halibut, to large catcher processors, which catch and process pollock in the Bering Sea (NPFMC 2012).

The Alaska region is an important area to study with regard to cross-fishery participation because (1) permit holders in Alaska fisheries often hold permits for more than one fishery (Sethi et al. 2014b); (2) there is concern over how regulatory changes affecting fishery participation impact Alaskan fishing communities (Carothers et al. 2010, Knapp 2011, Carothers 2013), particularly because Alaskan fisheries are considered at high risk for catch and revenue variability (Sethi et al. 2012); and (3) fishery portfolios in Alaska have become increasingly less diverse over time, and as a result, variability of individual- and community-level fishing income has increased (Kasperski and Holland 2013, Sethi et al. 2014a, Sethi et al. 2014b).

The existing literature on fishery participation in Alaska has documented individual and community fishing permit and landing portfolio diversification over time. For example, Sethi et al. (2014b) develop a metric-based approach to monitor the status of Alaska fishing communities over time, and show that both the average number of permits held within a community and the average number of permits held by a permit holder have declined over the past two decades. Carothers et al. (2010) and Knapp (2011) show that there has been a disappearance of fishing permits from rural Alaskan communities since the implementation of rights-based fishery policies, such as limited-entry programs in the salmon fisheries and individual fishing quotas in the halibut fishery. Other work has focused on the stabilizing role of fishery diversification on fishing revenues. For example, Kasperski and Holland (2013) show that income stemming from multiple fisheries in Alaska and Washington has become increasingly less diverse over time, and as a result, variability of income from fishing has increased. Sethi et al. (2014a) provide evidence that both fishery portfolio size and diversification play important roles in stabilizing community-level fishing revenues.

2.2. Data

Any individual that participates in commercial fishing activity in State of Alaska waters, including harvesting or landing catch from a state- or federally-managed fishery, requires a fishery-specific permit issued by the Alaska Commercial Fisheries Entry Commission (CFEC). CFEC permits are fishery-specific, with fisheries defined as area, gear, and species combinations. In 1973, entry into a subset of Alaskan commercial fisheries was limited with the goal of conserving Alaska’s fishery resources. A fixed number of permanent limited-entry permits were issued. These permits must be renewed annually, regardless of whether the permit holder chooses to participate in the fishery for which they are permitted. If the permit holder elects not to fish the permit or fails to renew it, the permit is removed from the fishery and not reissued. At present, limited-entry permits cannot be leased except in medical emergencies; however, they may be transferred or sold to other individuals by the permit holder. The CFEC also issues interim-use permits to individuals wanting to access other non-limited Alaska commercial fisheries or to limited-entry applicants awaiting qualification for permanent permits. Interim-use permits are issued annually for non-limited entry commercial fisheries and are not fixed in number.

Our analysis is based on the CFEC's publicly available database of fishery permits (available at: https://www.cfec.state.ak.us/fishery_statistics/permits.htm). Permit registration information in the CFEC database includes both identifying information about the permit holder and permit specific details including the fishery to which the permit grants entry, and the status (current/former owner), type (permanent, interim, transferable), and ownership sequence of the permit. In addition, we assign each fishery to a management jurisdiction (state or federal) and a geographic extent (regional or statewide).[2] We examine average permitting patterns over the past 10 years since the last major catch share program was implemented in Alaska (2006-2015) to provide a recent representation of cross-fishery participation in Alaska.[3] We also use data from 2004 and 2005 to investigate cross-fishery permit flows with the introduction of ITQs in the BBK fishery.[4]

2.3. Methods

We use analytical and visualization methods derived from network theory, which is conducive to studying relationships amongst discrete objects within complex systems. Similar approaches that focus on understanding associations and connectivity within a complex system have been applied to social-environmental systems (e.g., Dee et al. (2017)) and in multiple contexts within the fisheries domain, including: information-sharing and social interactions

[2] Note that for some CFEC fishery designations, particularly for the groundfish fisheries, a single CFEC permit can be used to fish in both a federal and state fishery. For these fisheries, we designate a CFEC fishery as "federally managed" if the fishery has a significant federal component to it, based on harvest specification tables for the federally-managed groundfish fisheries (see https://alaskafisheries.noaa.gov/harvest-specifications/field_harvest_spec_year/2016-2017-751). A more quantitive approach for assigning federal management designations would require landings data, which are not publicly available.

[3] Due to changes in CFEC fishery designations over the period of analysis, we group some fisheries to form a consistent time series. There are 113 fisheries included in the 2006-2015 analysis. Fisheries with fewer than five permit holders were dropped. See the Appendix for more details and for a list of all fisheries and their management and geographic designations.

[4] There are 114 fisheries and 116 fisheries included in the analysis in 2004 and 2005, respectively. Fisheries with fewer than five permit holders were dropped.

between fishery stakeholders (e.g., Barnes et al. (2016)), governance networks and regulatory processes (e.g., Hartley (2010) and Mulvaney et al. (2015)), and international seafood trade flows (e.g., Gephart and Pace (2015)). Network analyses in these settings are conducted to illustrate properties of social, regulatory, or trade connectivity. We employ a similar conceptual framework of fisheries connectivity to Bodin (2017) and Fuller et al. (2017) and similar network theory methods and statistics to Fuller et al. (2017), but focus on whether connectivity between Alaska's fisheries identifies the potential for cross-fishery spillovers from single-fishery policies. For calculations and figures, we use the free open-source graph visualization program Gephi.

2.3.1. The Network

A network can be represented as a graph consisting of a set of nodes (V) and edges (E), defined formally as $G = (V, E)$. In a binary (or unweighted) graph, each fishery is a node, where the size of a node represents the number of permit holders in a fishery, and an edge between two nodes is a binary measure indicating whether joint permitting between two fisheries exists or not. In a weighted graph, each edge also has an associated value. We depict the Alaska fisheries network as a weighted graph, where the weight of an edge represents the number of individuals permitted in both of the adjoined fisheries.[5]

The traditional representation of cross-participation between fisheries—i.e., a cross-tabulation matrix of fishery participation (Figure 1, Radtke and Davis (2000), and (NPFMC 2012))—has a network analog. In graph theory, the cross-tabulation matrix can be viewed as a weighted adjacency matrix, associated with a weighted graph. For example, Fishery A and Fishery B in Figure 1 share 10 permit holders, so we would represent cross-fishery permitting between these two fisheries with an edge weight of 10 connecting the two nodes.

We model the Alaska fishery system using the average number of fishermen permitted in a fishery between 2006 and 2015, and analyze the full network comprised of all Alaska fisheries, along with the following four "sub-networks": 1) a sub-network comprised of fisheries that are primarily federally managed; 2) a sub-network comprised of fisheries that are managed by the State of Alaska; 3) a sub-network comprised of fisheries with a statewide geographic extent; and 4) a sub-network comprised of fisheries with a regional (i.e., not statewide) geographic extent.

[5] In traditional social network analysis (SNA), one might define a node as an individual and an edge as a friendship or other type of connection between two individuals. In other social science work, nodes have represented publications and edges have connected a publication with those it cites (e.g. Hopcroft et al. (2004)). Examples of weighted networks include a network of colloborations between authors where the weights represent number of co-authored publications and a network of air transportiation where the weights represent number of flights along particular routes (Barrat et al. 2004).

The purpose for examining state and federal fisheries as separate sub-networks is to determine whether cross-fishery permitting may differ by management jurisdiction. Further, network statistics can yield insight into cross-fishery permitting between each sub-network by looking at the difference between the full network and the jurisdiction-specific networks. For example, comparing measures of fishery connectedness between the full network and the jurisdiction-specific networks provides information on spillover potential from federal to state fisheries (and vice versa) after a single-fishery policy implementation. Understanding the potential for spillover between state and federal fisheries is highly relevant from a policy perspective since the federal and state governments are responsible for their own management program design and evaluation, and do not necessarily consider impacts beyond their jurisdiction. For example, federal management documents that do calculate cross tabulations (e.g. NPFMC (2012)) only do so for federal fisheries.

Similarly, the purpose of considering regional and statewide fisheries as separate networks is to determine the potential geographic scope of single fishery policy spillovers. For instance, if some or all statewide fisheries are only permitted by a subset of fishermen from a particular region, a change in a statewide fishery policy may not have significant impacts on fishermen and fisheries in other regions. If, on the other hand, statewide fisheries are fished by fishermen from a large set of regions, the potential geographic scope of impacts would be larger.

Finally, we construct networks of Alaska fishery interconnectedness before and after ITQ introduction in the BBK fishery. We compare the cross-participation in these two static networks and examine the flow of permits that occurred after ITQs were introduced. This case study provides an example of how network methods and statistics can be used to examine the impact of a management change on cross-participation, and examines the extent to which ex-ante network statistics can identify the ex-post spillover from implementing a single-fishery management change.

2.3.2. Characterizing Network Topology

We consider a range of commonly used indicators that include both aggregate measures of an entire network, as well as node-specific measures of fishery connectedness in the network. Aggregate network statistics provide information on characteristics of the entire graph. A basic aggregate statistic is a binary measure of whether the graph is connected, meaning all fisheries (nodes) are reachable via a path (i.e., a set of edges) from any other fishery. If the graph is not connected, then there exist disconnected subgraphs, or portions of the network, that are unconnected from other portions. The fisheries in a disconnected subgraph do not share permit holders with the subset of fisheries outside of the subgraph, and would therefore be unlikely to experience spillover impacts from a policy change in a fishery outside the subgraph. The smallest possible disconnected subgraph is an unconnected fishery, within which a permit holder holds a permit for only that fishery.

Network density is an aggregate network statistic that measures the degree of network connectivity, which in our case represents the extent to which fisheries share permit holders. Network density is calculated by dividing the number of edges present in the network by the total number of possible edges. The total number of possible edges is $N \times (N\text{-}1)/2$, where N is the total number of nodes. The actual number of edges equals the number of pairs of fisheries that share at least one permit holder in one of the years 2006-2015. A network's density can be interpreted as the proportion of all fishery pairs that have at least one common permit holder; thus, a network with low density is comprised of relatively few jointly-permitted fisheries, representing a relatively unconnected network. Network density is useful for describing interconnectedness because it controls for the number of fisheries in the network, which is important when comparing connectivity among subsets of fisheries (e.g., statewide and regional fisheries). However, density is limited because it does not consider the number of permit holders that are jointly permitted in other fisheries.

Node-specific statistics are informative on their own and can also be aggregated to yield insight into the entire network. We focus on node size, average edge weight, degree, and node closeness centrality. Node size is calculated as the average number of permit holders in a fishery. The average edge weight for a given node equals the average weight across all the edges connected to the node (e.g., in Figure 1 the average edge weight of Fishery A equals 10; the average edge weight of Fishery B equals 40. Average edge weight for a fishery therefore equals the average number of permit holders a fishery shares with another fishery it is connected to. The average edge weight across all edges in the network provides aggregate information on average joint-permitting across all pairs of connected fisheries in the network.[6]

The degree of each fishery is the number of other fisheries that it is directly connected via an edge. A node with a high degree represents a fishery that is jointly permitted with many other fisheries. In contrast, a node with low degree represents a fishery comprised of fishermen (potentially many) that rarely hold permits in other fisheries, and therefore displays little (if any) joint permitting with other fisheries. The average degree of the network is the average of the

[6] When calculating the aggregate average edge weight, pairs of fisheries that have no joint permit holders are not included.

degree across all network nodes. While node degree provides information on the extent of a fishery's first-degree connections, it may provide only limited information on the potential scope of a policy spillover because it does not consider fishery connections beyond the first degree.

Node closeness centrality measures how connected a fishery is to all other fisheries in a connected graph. The paths through which one fishery can be reached from other fisheries can be thought of as a potential chain of spillover impacts. Calculation of node closeness centrality relies on the distance, or path length, between two nodes, which is equal to the minimum number of edges one must transverse to connect the two nodes. For example, if two fisheries share at least one permit holder, such as fisheries A and B in Figure 1, the distance between the two nodes is one, whereas the distance between fisheries A and C is equal to two. This measure of connectedness is an extension to basic cross tabulations because it goes beyond first-degree connections, thereby capturing the potential for spillover impacts to spread beyond directly-connected fisheries through a chain of spillover impacts. Letting $d(v_i,v_j)$ denote the distance between nodes i and j, the closeness centrality of a node i is given by:

$$closeness\ centrality_i = \frac{N-1}{\sum_{j=1, j\neq i}^{N} d(v_i, v_j)},$$

which is the inverse of the average distance between a node and all other nodes. The closeness centrality is between zero and one. If a fishery is directly connected to every other fishery via an edge, its closeness centrality will be one; on the other hand, if a fishery shares relatively few edges with other fisheries, the distance between nodes will be higher and the closeness centrality will gravitate towards zero. For example, if a fishery shares permit holders with many other fisheries, and in addition, those permit holders also share connections with the remaining fisheries, then that fishery would have a large measure of closeness centrality. We calculate average node centrality over the network by averaging the node centrality across all nodes in the network. This provides information at the network level on how connected fisheries are to other fisheries, considering both direct connectivity (two fisheries sharing permit holders) as well as indirect connectivity (the extent to which a fishery shares permit holder with fisheries that also share permit holders with other fisheries, and so on).

2.3.3. Cluster Analysis

We use cluster analysis to partition the network into clusters of fisheries that exhibit high levels of cross-fishery permitting within the cluster, but relatively low cross-fishery permitting with fisheries outside the cluster. A fishery cluster therefore represents a set of fisheries from which fishermen choose when making permitting decisions, and thus likely represents historical fishery substitution possibilities. Intuitively, a fishery cluster represents the likely scope for potential spillover effects from a single-fishery policy.

We identify clusters using a modularity-based community detection algorithm to statistically partition the network into clusters of fisheries (Blondel et al. 2008).[7] We then analyze clusters in terms of node and aggregate network characteristics, such as connectivity and node centrality within the cluster, and the extent to which fishery characteristics are associated with cluster membership.[8] Specifically, we examine the extent to which cluster membership is more common between fisheries that are geographically close, are fished using the same gear, have a similar target species, and/or fall under federal or state jurisdiction. Fishery characteristics that are good predictors of cluster membership aid in the identification of fisheries that may or may not be susceptible to spillover effects from a single fishery policy.

To analyze cluster membership in terms of fishery characteristics, we estimate the probability that two fisheries belong to the same cluster as a function of sharing fishery characteristics. Specifically, for each potential fishery pair in the network, we calculate a binary variable *cluster* equal to one if the fisheries are in the same cluster, and zero if not.[9] Additionally, we create separate binary variables indicating whether each pair of fisheries share a common fishing gear, geographic area, and target species. We then estimate the probability that the fisheries in pair *i* belong to the same cluster as a function of sharing the same gear, geographic area, and/or target species using the following logistic regression model:

$$Pr(cluster_i = 1) = F(\beta_0 + \beta_1 gear_i + \beta_2 area_i + \beta_3 species_i),$$

---

[7] Clusters are groups of nodes in a network that are characterized by a high density of internal connections and low density of external connections. Modularity, Q, is the optimand for the Louvain cluster detection algorithm we employ. It is determined by the ratio of the number of edges within clusters to the number of edges between clusters across a network (Newman 2004). The number of clusters and assignment of nodes to clusters are chosen to maximize network modularity. This partitions the network into clusters of nodes with higher edge representation than had edges been assigned to the graph randomly. Cluster identification is used in a variety of fields to determine functional groups to simplify complex networks for decision-making (Danon et al. 2005).

[8] Network and node statistics parallel those presented for the aggregate network, but are calculated for only those fisheries within a cluster.

[9] Note that we combine CFEC species, gear, and area codes into more aggregated groups to facilitate the analysis of clustering patterns. After dropping fisheries where a gear, area, or species attribute is "other", we end up with 99 fisheries, which results in 4,851 fishery pairs (see Appendix for additional detail). We treat the statewide designation as its own area code.

where $F(z) = e^z/(1 + e^z)$ is the cumulative logistic distribution. We then calculate each characteristic's independent influence on cluster membership as the average marginal effect of sharing a characteristic on the probability that two fisheries belong to the same cluster. For example, fishing gear's influence on cluster membership is calculated as:

$$\overline{Pr}(cluster_i = 1|gear = 1) - \overline{Pr}(cluster_i = 1|gear = 0),$$

where $\overline{Pr}$ denotes the average predicted probability from the logistic regression.

2.3.4. Characterizing Spillover

We use the introduction of ITQs in the BBK fishery in 2005 as a means of exploring how network methodology can be used to characterize joint permitting pre- and post-management change, as well as examine spillover following a policy implementation.[10] We focus on spillover along the extensive margin—i.e., exit and entry decisions—because: 1) exit and entry are relatively well-studied decisions and documented in the fishery management literature (e.g., Brinson and Thunberg (2016)); and 2) our data does not allow us to measure behavioral changes along the intensive margin, such as changes in fishing effort in non-target fisheries.[11] We identify five types of permit-holder behavior coinciding with the ITQ (Figure 5): permit holders who remain permitted in the BBK fishery; permit holders who exit the BBK fishery and who have no other permits in other Alaska fisheries (these permit holders are determined to exit the region); permit holders who exit the BBK fishery and do not change their fishing portfolio (i.e., do not obtain permits in new fisheries); permit holders who exit the BBK fishery and change their fishing portfolio by obtaining permits in new fisheries; and permit holders who enter the BBK fishery. Focusing on the permit holders who exit the BBK fishery and obtain permits in new fisheries, we determine the proportion of these new fisheries that were in the preexisting BBK network and compute the correlation between pre-ITQ edge weight and number of permit acquisitions for those fisheries in the preexisting BBK network.

[10] For more information on the fishery and post-management changes see (Fina 2005) and Reimer et al. (2014).

[11] In general, there are several behavioral margins across which fishers can respond to a policy change (Smith 2012, Reimer et al. 2014).

3. Results and Discussion

3.1. Network Statistics

Table 1 (row 1) presents statistics for the full network of Alaska fisheries and Figure 2 provides a visual representation of the network from 2006-2015, where the size of a node scales with the average number of permit holders in a fishery and the thickness of an edge represents the average number of fishermen jointly permitted in the two fisheries.[12] Both indicate that Alaska fisheries are very connected through the cross-fishery permitting behavior of fishermen. Indeed, all but one of the 113 fisheries form a connected graph and are therefore able to be reached via a path from all other fisheries.[13] Network density indicates that approximately one-third of all possible edges are present, implying that one in three fisheries pairs are directly connected through joint permitting, on average. Network degree indicates that the average fishery shares permit holders with approximately 35 other fisheries, while average edge weight indicates that a connected pair of fisheries share nearly 6 permit holders, on average. Altogether, these statistics suggest that there is considerable potential for spillovers across fisheries in the Alaska region.

The statistics in Table 2 indicate that larger fisheries (i.e., higher node size) that share relatively more permit holders with other fisheries (i.e., more edges, higher edge weight) and have higher closeness centrality often appear at the core, or center, of the network. For example, the statewide halibut longline fishery (B06B), which appears at the center of Figure 2, is the largest fishery in terms of number of permit holders, has the highest closeness centrality, and has the highest degree in the full Alaska fisheries network. In contrast, fisheries with lower node-level statistics tend to be located on the periphery of the network and not directly connected to the core fisheries. For example, the scallop dredge fishery (W22BV), which has only 6 permit holders and an extremely low closeness centrality (0.39) and average edge weight (less than 1), is not connected to any of the core fisheries listed in Table 2.

The large measures of centrality common to many of the core fisheries are primarily driven by two mechanisms, which together have important spillover implications. First, the central fisheries have many direct, or first-order, connections with other fisheries through joint permitting, as measured by node degree. Indeed, the four fisheries with the highest closeness

[12] The layout of the fisheries in Figure 2 is based on an algorithm that takes into account the presence and weight of edge relationships in order to represent relative connectivity of nodes. Node characteristics, such as the number of permit holders and fishery characteristics, are not considered, though node arrangement may reveal trends about the characteristics of fisheries that are more central to the aggregate network.

[13] The single disconnected fishery in the full network is the Bering Sea Korean hair crab pot gear fishery (E91QV).

centrality are also the four nodes with the highest degree. Second, many of the central fisheries are directly connected to one another (Figure 2), creating indirect connections between fisheries that do not directly share permit holders. Together, the direct and indirect connectivity creates a network in which spillover from a single-fishery policy in a core fishery could impact both other core and periphery fisheries. Further, given that many of the most central fisheries are also some of the largest and have the highest edge weights, both the scope and the magnitude of single-fishery policy spillovers from core fisheries have the potential to be large.

Network statistics for the four different sub-networks we consider (Table 1, rows 2-5) indicate that considerable heterogeneity exists between the sub-networks. Indeed, many federally-managed and statewide fisheries appear at the core of the network and differ in their connectivity relative to state-managed and regional fisheries.[14] The statewide and federally-managed fisheries each a density, edge-weight, and closeness centrality that are considerably larger than those of the regional and state-managed networks, suggesting that single-fishery policies in federal and statewide fisheries may be likely to generate substantial direct spillover across fisheries within their own respective networks. However, the substantial joint-permitting across the four sub-networks suggests that spillovers are not likely to be contained within a single sub-network (Table 3). Out of the 1,994 edges that comprise the entire network, 773 edges (~39%) connect statewide fisheries to regional fisheries. Further, the 2,002 possible edges between statewide and regional fisheries implies that 39% of all possible regional-statewide fishery pairs are connected through joint permitting. Edges connecting state-managed to federally-managed fisheries also make up a significant portion of the total number of edges in the full network (453 out of 1,994 edges, or 23%) and have large average edge weight—on average, there are 10.3 permit holders per federal-state fishery pair. Further, 38% of all possible state-federal fishery pairs are connected through joint permitting. Altogether, these findings suggest that single-fishery policies in federal and/or statewide fisheries have the potential to spill over into state-managed and/or regional fisheries (and vice versa). Therefore, spillover impacts on fisheries under other jurisdictions and in other regions may need to be considered in order to estimate the full impact of a policy change.

---

[14] Note that although many federal fisheries cover statewide areal extents, there is not a one-to-one correspondence between these two designations. See Appendix for network figures of each of the four jurisdiction- and geographic-specific networks.

3.2. Cluster Analysis

The modularity-based community detection algorithm identified seven clusters of fisheries that are relatively disconnected from fisheries in the other clusters: five clusters that contain between 5 and 37 fisheries, and two clusters that contain only one fishery each (Table 4).[15] Cluster 1 is the largest cluster in terms of the number of fisheries (37), is the most internally connected, as measured by its density, average node degree, and average centrality, and contains some of the most central fisheries in the full network—e.g., the federally managed statewide halibut and sablefish longline fisheries, the federally managed longline groundfish fisheries, the state-managed salmon troll fishery, and the southeast king crab pot fisheries. Cluster 2 contains a significant number of pot gear fisheries targeting groundfish and crab—e.g., the federally managed groundfish pot fishery, the statewide groundfish jig fishery, and the BBK fishery. The fisheries that comprise Clusters 3 and 4 are geographically grouped, with Cluster 3 being dominated by fisheries in southcentral and southeast Alaska—e.g., Prince William Sound herring and shrimp pot fisheries and the Cook Inlet setnet salmon fishery—and Cluster 4 being primarily comprised of fisheries in west and northwest Alaska—e.g., Bristol Bay salmon fisheries, salmon and herring fisheries in Kuskokwim Bay and Norton Sound. Cluster 5 consists of only dive fisheries, which do not appear in any other cluster, while Clusters 6 and 7 are single-fishery clusters--the Bering Sea Korean hair crab pot fishery and the vessel-permitted scallop dredge fishery.

Using the output from the logistic regression model, we reject the null hypotheses that sharing a geographic area (p-value = 0.000) and sharing a fishing gear (p-value = 0.000) do not have a marginal effect on the probability of being a member of the same cluster (Table 5). Of the fishery pairs that share the same area (gear, species), 55% (34%, 23%) of fishery pairs are predicted to be in the same cluster, whereas among the fishery pairs that do not share an area (gear, species), only 16% (23%, 25%) are predicted to be in the same cluster. Thus, sharing the same geographic area increases the probability of being in the same cluster by 0.387 percentage points (from .162 to .549), which is considerably more than sharing a species (-0.0219) or gear type (0.108). This finding can be seen visually as well in Figure 3, where we map fisheries based on geographic location and cluster membership. Thus, geographic proximity is likely a natural

[15] We find that several clustering variants fall within the tolerance of Gephi's optimization routine. We rerun the optimization program and find the clusters are very robust (generally less than 5% of fisheries, which generally have low centrality, move clusters) with one exception. In cases with fewer clusters the dive fisheries sometimes appear in Cluster 1 or as split apart in Clusters 1 and 2. This pattern holds if we increase the resolution, thus decreasing the number of clusters. For our analysis we keep the dive fisheries as their own cluster.

starting point for identifying fisheries that could be susceptible to a single-fishery policy, a result that is consistent with previous work indicating that a fishing community's fishery portfolio may be predetermined by the set of local fishing opportunities (Sethi et al. 2014a).

3.3. Spillover Case Study: ITQs in the Bristol Bay King Crab Pot Fishery

In Figure 4 we present the network for the BBK fishery in 2004 prior to the introduction of ITQs (panel (a)) and the change in permits between 2004 and 2005 with the onset of ITQs (panel (b)). The most notable change was the shrinking of the BBK fishery node size (labeled K09T), reflecting the decrease in permit holders from 266 to 136 between 2004 and 2005. Of the 136 permit holders in 2005, 124 were permitted in the fishery prior to ITQs and 12 were new entrants, implying that 142 permit holders exited the fishery after ITQs (Figure 5). Of those permit holders that exited the fishery, 35 did not hold permits in any Alaska fishery in the following year, 66 did not change their permit holdings in other fisheries, and 41 acquired a total of 62 permits in other fisheries. The large amount of exiting resulted in a considerable drop in cross-participation between the BBK fishery and other fisheries after ITQs. However, while the average edge weight of the fishery decreased (from 12.4 in 2004 to 8.3 in 2005), there was not a significant change in the number of connected fisheries (degree is 42 in 2004 and 40 in 2005) or its overall connectivity to the network (closeness centrality is 0.60 in 2004 and 0.59 in 2005). Thus, exit from the BBK fishery was relatively proportional to the joint-permitting pattern that existed prior to ITQ introduction.

To explore whether ITQs in the BBK fishery generated spillover into non-target fisheries, we focus on the 41 permit holders that exited the BBK fishery and acquired permits in new fisheries.[16] This set of permit holders obtained 62 new permits in 21 fisheries (Figure 4 panel (b)), ranging from 13 permits in the Bering Sea Tanner crab pot fishery (T09Q) to 1 permit in several other fisheries. While determining the magnitude of impacts in non-target fisheries from spillover is beyond the scope of this paper, any impact likely depends on the characteristics of the non-target fisheries, such as the number of permit holders. For example, the addition of 7 permit holders in the Statewide miscellaneous saltwater finfish longline (M06B) fisheries

---

[16] In focusing on this set of permits, we explore permitting changes that coincided with the onset of ITQs. We leave for future work a full causal estimation of the spillover, which requires identifying the counterfactual spillover that would have occurred if the management change did not occur. The relatively high magnitude of new permit acquisitions that coincides with the introduction of ITQs in the BBK fishery, however, suggests that much of this resposnse is due to the ITQ program, as opposed to a simultaneous shock or individual motivations on the part of the permit holder. Information on prior entry and exit of permit holders from the BBK fishery is available in the Appendix.

represents only a 1% increase in the number of permit holders in these fisheries, and therefore did not likely have much of an impact on preexisting permit holders. In contrast, the Bering Sea King crab pot fishery (K09Q) gained two permit holders from the BBK fishery, bringing its total number of permit holders in 2005 to ten, an increase of 25%.

One of the potential benefits of network methodology is its capability of predicting the scope of spillover from a policy change. As an example, to what extent is the pre-ITQ network (Figure 4 panel (a)) able to predict the flow of permit holders after ITQ introduction in the BBK fishery (Figure 4 panel (b))? Much of the change in permit holding coinciding with the ITQ program is well-correlated with the pre-ITQ network structure and statistics. Prior cross-fishery participation is a good predictor of where exiters of the BBK crab fishery enter. Of the 21 fisheries receiving new permit holders, 18 shared permit holders with the BBK fishery in 2004. Only 2% of fisheries that did not share a prior connection with the target fishery received exiters, while 40% of fisheries that did share a prior connection with the target fishery received exiters. There is also evidence that the number of shared permit holders with the BBK fishery is a good predictor of spillover; indeed, a positive correlation of 0.8 exists between the edge weight for fisheries connected to the BBK fishery and the number of new permit acquisitions. For example, pre-ITQ, the BBK fishery shared the highest edge weight with the Bering Sea Tanner crab pot fishery (T09Q), which also received the highest number of exiters (13) from BBK post-ITQ. Overall, this example demonstrates that network statistics, such as the degree and edge weights associated with a fishery undergoing a policy change, can be useful for identifying the potential scope for cross-fishery spillover.

4. Conclusion

Representing a complex system of fisheries as a network leads to a novel characterization of cross-fishery permitting that has the potential to inform policy design and to identify fisheries that are susceptible to spillovers from single-fishery policies. Our results demonstrate that cross-fishery permitting in Alaska is substantial, spanning multiple management jurisdictions (federal and state), species, geographic areas, and gear types. Several large federal and statewide fisheries are central to the network, providing a means for nearly all fisheries in the network to be connected to one another, either directly through joint permitting, or indirectly through connected paths of jointly-permitted fisheries. On one hand, the significant cross-fishery permitting makes it likely that management changes in one fishery could have far reaching spillover effects on other fisheries and the fishermen and communities associated with these fisheries. On the other hand, there is heterogeneity in cross-fishery permitting that likely makes some fisheries more susceptible than others to policy changes in other fisheries.

Several insights regarding cross-fishery permitting emerge from our analysis. First, federal and statewide fisheries generally have the highest levels of cross-fishery permitting and are the most central fisheries in the network, making them the most likely candidates for generating spillover from single-fishery policies. Second, we find significant cross-fishery permitting between federal and state fisheries, which highlights the importance of considering potential impacts on state fisheries when designing and evaluating federal fishery management policy, and vice versa. Third, clusters of well-connected fisheries tend to be composed of fisheries within adjacent geographic areas, suggesting that geographically similar fisheries may be a good place to look for potential spillover effects from a management change. Finally, preexisting network structure and statistics can be useful for identifying the potential scope of policy-induced spillovers, as demonstrated by our investigation of the spillover coinciding with the ITQ program on the BBK fishery.

From a policy perspective, establishing baseline information on cross-fishery permitting using network theory provides useful information to fishery managers and stakeholders in developing a data-driven scope of fisheries and permit holders that are likely to be impacted by proposed polices. However, the approach we present in this paper is limited in several respects, and work remains before spillover effects from past and future single-fishery policies can be fully evaluated and predicted. One area of future work concerns the fact that the data used in our analysis contains information solely on permitting behavior, not fishing behavior (which is confidential). In fact, several permits go unfished in any given year—a phenomenon often known as "permit latency" (CFEC 2015). Therefore, spillover effects of single-fishery policies would be better understood by examining permitting behavior and fishing effort (e.g., landings, days fished) jointly. Another challenge is that retrospective evaluations of spillover effects from previous policies require both a time series of network statistics and a strategy for isolating policy-induced effects from other shocks that affect the evolution of the network. Other shocks that could impact fishermen behavior include stock changes, that in turn could result in changes to fishing season length and timing, which could influence cross-fishery permitting and participation (Radtke and Davis 2000). Methods for estimating network statistics over time and for causal policy evaluations have yet to be applied within a fisheries context. Lastly, permitting behavior in the past is influenced by the prevailing institutions governing fisheries at that time. For instance, many of Alaska state fisheries are governed by limited-entry programs, which likely have the effect of reducing joint permitting to levels below those that would exist if those fisheries were open access. If a policy change influences the rules governing cross-fishery participation, then future permitting behavior will not necessarily be the same as it was in the past. In such a case, predicting the potential spillover effects from a single-fishery policy will require a more mechanistic approach that is able to predict how fishermen make permitting decisions and how these choices will change in response to a new policy.

Although more work is required to fully operationalize the potential for network methods to inform fisheries policy, a network approach has the potential to contribute to efforts evaluating socioeconomic impacts of ecosystem-based fisheries management (EBFM). EBFM programs are increasingly being adopted around the world yet the magnitude and sign of social and economic impacts of EBFM are unknown (Marshall et al 2017). Prior work has shown that aggregate revenues can be increased and their variance decreased by taking an ecosystem-based approach when setting catch levels (Sanchirico et al. 2008); a network-based approach to characterizing cross-fishery permitting could improve our understanding of how changing catch levels could impact fishermen.

References

Anderson S. C., E. J. Ward, A. O. Shelton, M. D. Adkison, A. H. Beaudreau, R. E. Brenner, A. C. Haynie, J. C. Shriver, J. T. Watson and B. C. Williams. 2017. Benefits and Risks of Diversification for Individual Fishers. *Proceedings of the National Academy of Sciences* **114**(40): 10797-10802.

Asche F., D. V. Gordon, C. L. Jensen, S. U. Rashid, G. R. Munro and J. G. Sutinen. 2007. Individual Vessel Quotas and Increased Fishing Pressure on Unregulated Species. *Land Economics* **83**(1): 41-49.

Barnes M. L., J. Lynham, K. Kalberg and P. Leung. 2016. Social Networks and Environmental Outcomes. *Proceedings of the National Academy of Sciences* **113**(23): 6466-6471.

Barrat A., M. Barthelemy, R. Pastor-Satorras and A. Vespignani. 2004. The Architecture of Complex Weighted Networks. *Proceedings of the National Academy of Sciences of the United States of America* **101**(11): 3747-3752.

Blondel V. D., J. L. Guillaume, R. Lambiotte and E. Lefebvre. 2008. Fast Unfolding of Communities in Large Networks. *Journal of Statistical Mechanics-Theory and Experiment*.

Bodin Ö. 2017. Collaborative Environmental Governance: Achieving Collective Action in Social-Ecological Systems. *Science* **357**(6352).

Brinson A. A. and E. M. Thunberg. 2016. Performance of Federally Managed Catch Share Fisheries in the United States. *Fisheries Research* **179**(Supplement C): 213-223.

Carothers C. 2013. A Survey of Us Halibut IFQ Holders: Market Participation, Attitudes, and Impacts. *Marine Policy* **38**(C): 515-522.

Carothers C., D. K. Lew and J. Sepez. 2010. Fishing Rights and Small Communities: Alaska Halibut IFQ Transfer Patterns. *Ocean & Coastal Management* **53**(9): 518-523.

CFEC. 2015. *CFEC Permit Holdings and Estimates of Gross Earnings in the Bristol Bay Commercial Salmon Fisheries, 1975-2014*. R. Section.

Cline T. J., D. E. Schindler and R. Hilborn. 2017. Fisheries Portfolio Diversification and Turnover Buffer Alaskan Fishing Communities from Abrupt Resource and Market Changes. *Nature Communications* **8**: 14042.

Cunningham S., L. S. Bennear and M. D. Smith. 2016. Spillovers in Regional Fisheries Management: Do Catch Shares Cause Leakage? *Land Economics* **92**(2): 344-362.

Danon L., A. Diaz-Guilera, J. Duch and A. Arenas. 2005. Comparing Community Structure Identification. *Journal of Statistical Mechanics: Theory and Experiment* **2005**(09): P09008.

Dee L. E., S. Allesina, A. Bonn, A. Eklof, S. D. Gaines, J. Hines, U. Jacob, E. Mcdonald-Madden, H. Possingham, M. Schroter and R. M. Thompson. 2017. Operationalizing Network Theory for Ecosystem Service Assessments. *Trends in Ecology & Evolution* **32**(2): 118-130.

Fina M. 2005. Rationalization of the Bering Sea and Aleutian Islands Crab Fisheries. *Marine Policy* **29**(4): 311-322.

Fuller E. C., J. F. Samhouri, J. S. Stoll, S. A. Levin and J. R. Watson. 2017. Characterizing Fisheries Connectivity in Marine Social–Ecological Systems. *ICES Journal of Marine Science* **74**(8): 2087-2096.

Gephart J. A. and M. L. Pace. 2015. Structure and Evolution of the Global Seafood Trade Network. *Environmental Research Letters* **10**(12): 125014.

Hartley T. W. 2010. Fishery Management as a Governance Network: Examples from the Gulf of Maine and the Potential for Communication Network Analysis Research in Fisheries. *Marine Policy* **34**(5): 1060-1067.

Hopcroft J., O. Khan, B. Kulis and B. Selman. 2004. Tracking Evolving Communities in Large Linked Networks. *Proceedings of the National Academy of Sciences* **101**(suppl 1): 5249-5253.

Hutniczak B. 2014. Increasing Pressure on Unregulated Species Due to Changes in Individual Vessel Quotas: An Empirical Application to Trawler Fishing in the Baltic Sea. *Marine Resource Economics* **29**(3): 201-217.

Kasperski S. and D. S. Holland. 2013. Income Diversification and Risk for Fishermen. *Proceedings of the National Academy of Sciences* **110**(6): 2076-2081.

Knapp G. 2011. Local Permit Ownership in Alaska Salmon Fisheries. *Marine Policy* **35**(5): 658-666.

Mulvaney K. K., S. Lee, T. O. Höök and L. S. Prokopy. 2015. Casting a Net to Better Understand Fisheries Management: An Affiliation Network Analysis of the Great Lakes Fishery Commission. *Marine Policy* **57**: 120-131.

Newman M. E. 2004. Fast Algorithm for Detecting Community Structure in Networks. *Physical review E* **69**(6): 066133.

NPFMC. 2012. *Fishing Fleet Profiles*. North Pacific Fishery Management Council. **2017**.

Radtke H. D. and S. W. Davis. 2000. *Description of U.S. West Coast Commercial Fishing Fleet and Seafood Processors*. PSMFC.

Reimer M. N., J. K. Abbott and J. E. Wilen. 2014. Unraveling the Multiple Margins of Rent Generation from Individual Transferable Quotas. *Land Economics* **90**(3): 538-559.

Sanchirico J. N., M. D. Smith and D. W. Lipton. 2008. An Empirical Approach to Ecosystem-Based Fishery Management. *Ecological Economics* **64**(3): 586-596.

Sethi S. A., M. Dalton and R. Hilborn. 2012. Quantitative Risk Measures Applied to Alaskan Commercial Fisheries. *Canadian Journal of Fisheries and Aquatic Sciences* **69**(3): 487-498.

Sethi S. A., M. N. Reimer and G. Knapp. 2014a. Alaskan Fishing Community Revenues and the Stabilizing Role of Fishing Portfolios. *Marine Policy* **48**(C): 134-141.

Sethi S. A., W. Riggs and G. Knapp. 2014b. Metrics to Monitor the Status of Fishing Communities: An Alaska State of the State Retrospective 1980-2010. *Ocean & Coastal Management* **88**(c): 21-30.

Smith M. D. 2012. The New Fisheries Economics: Incentives across Many Margins. *Annual Review of Resource Economics* **4**(1): 379-402.

Tables and Figures

Figure 1: Cross-fishery permitting example: number of individuals permitted in each pair of fisheries. The adjacency matrix in Panel a is symmetric; diagonal values are total individuals permitted in each fishery; off-diagonals must be strictly less than row and column diagonal numbers (i.e., cross-permitting is less than or equal to the minimum number of individuals in the two fisheries). Panel b represents the same adjacency matrix as a network diagram.

(a)

	Fishery A	Fishery B	Fishery C	Fishery D
Fishery A	100	10	0	0
Fishery B	-	110	70	40
Fishery C	-	-	200	35
Fishery D	-	-	-	50

(b)

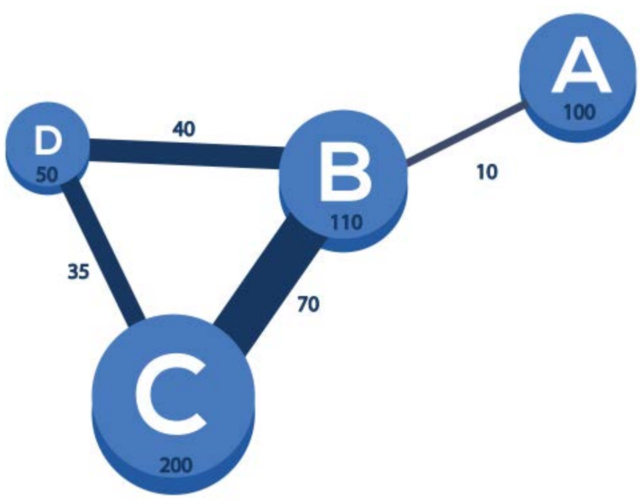
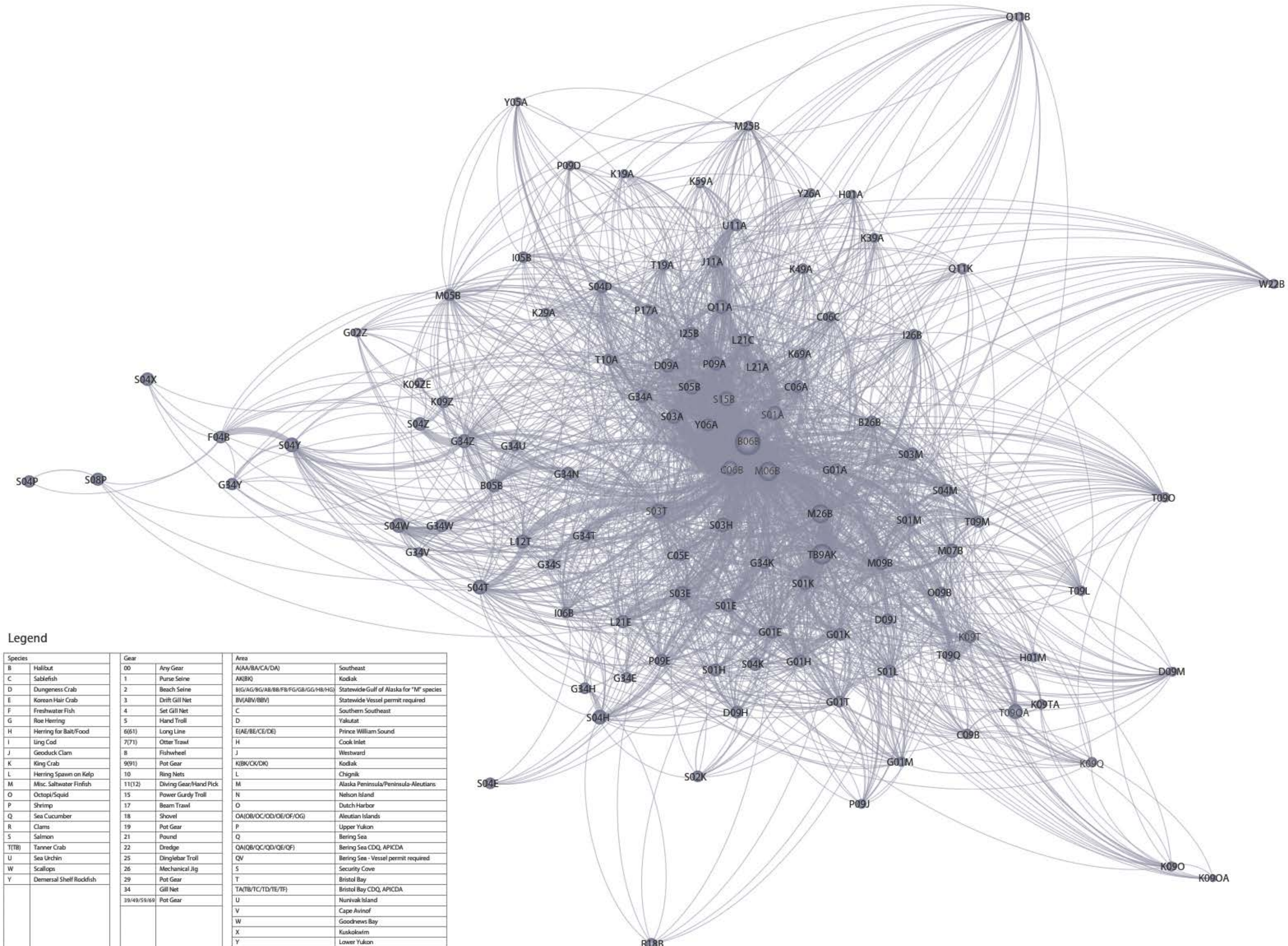


Figure 2: Cross-fishery permitting in the Alaska fishery network, 2006-2015. Nodes represent individual fisheries, with node size corresponding to the average number of permits held for that fishery. Edge thickness represents the average number of permit holders permitted in each of the two connected fisheries.
Note 1: Two nodes are excluded from this figure. One, E91QV, is not connected to the network. The second, W22BV, was plotted by the algorithm far away from the network but connected to three nodes. Both were removed to maintain graph clarity.
Note 2: As described in the text and the Appendix, in some instances we aggregated across CFEC codes to form a fishery unit for the analysis. These instances are shown in the table with the species, gear, and area designation used in Figure 2 to label the node listed first, followed by the codes that were aggregated to form the fishery unit for the analysis.



Legend

Species			Gear			Area	
B	Halibut		00	Any Gear		A(AA/BA/CA/DA)	Southeast
C	Sablefish		1	Purse Seine		AK(BK)	Kodiak
D	Dungeness Crab		2	Beach Seine		B(G/AG/BG/AB/BB/FB/FG/GB/GG/HB/HG)	Statewide Gulf of Alaska for "M" species
E	Korean Hair Crab		3	Drift Gill Net		BV(ABV/BBV)	Statewide Vessel permit required
F	Freshwater Fish		4	Set Gill Net		C	Southern Southeast
G	Roe Herring		5	Hand Troll		D	Yakutat
H	Herring for Bait/Food		6(61)	Long Line		E(AE/BE/CE/DE)	Prince William Sound
I	Ling Cod		7(71)	Otter Trawl		H	Cook Inlet
J	Geoduck Clam		8	Fishwheel		J	Westward
K	King Crab		9(91)	Pot Gear		K(BK/CK/DK)	Kodiak
L	Herring Spawn on Kelp		10	Ring Nets		L	Chignik
M	Misc. Saltwater Finfish		11(12)	Diving Gear/Hand Pick		M	Alaska Peninsula/Peninsula-Aleutians
O	Octopi/Squid		15	Power Gurdy Troll		N	Nelson Island
P	Shrimp		17	Beam Trawl		O	Dutch Harbor
Q	Sea Cucumber		18	Shovel		OA(OB/OC/OD/OE/OF/OG)	Aleutian Islands
R	Clams		19	Pot Gear		P	Upper Yukon
S	Salmon		21	Pound		Q	Bering Sea
T(TB)	Tanner Crab		22	Dredge		QA(QB/QC/QD/QE/QF)	Bering Sea CDQ, APICDA
U	Sea Urchin		25	Dinglebar Troll		QV	Bering Sea - Vessel permit required
W	Scallops		26	Mechanical Jig		S	Security Cove
Y	Demersal Shelf Rockfish		29	Pot Gear		T	Bristol Bay
			34	Gill Net		TA(TB/TC/TD/TE/TF)	Bristol Bay CDQ, APICDA
			39/49/59/69	Pot Gear		U	Nunivak Island
						V	Cape Avinof
						W	Goodnews Bay
						X	Kuskokwim
						Y	Lower Yukon
						Z	Norton Sound
						ZE(ZF)	Norton Sound CDQ, NSEDC

Figure 3: Geographic Location of Area-Designated Fisheries. Node size represents relative number of permits issued from 2006-2015 in each fishery. The colors represent the clusters from the cluster analysis. Nodes are placed in the approximate location of the associated fishable area. Note**:** Only clusters 1-5 appear in the figure.

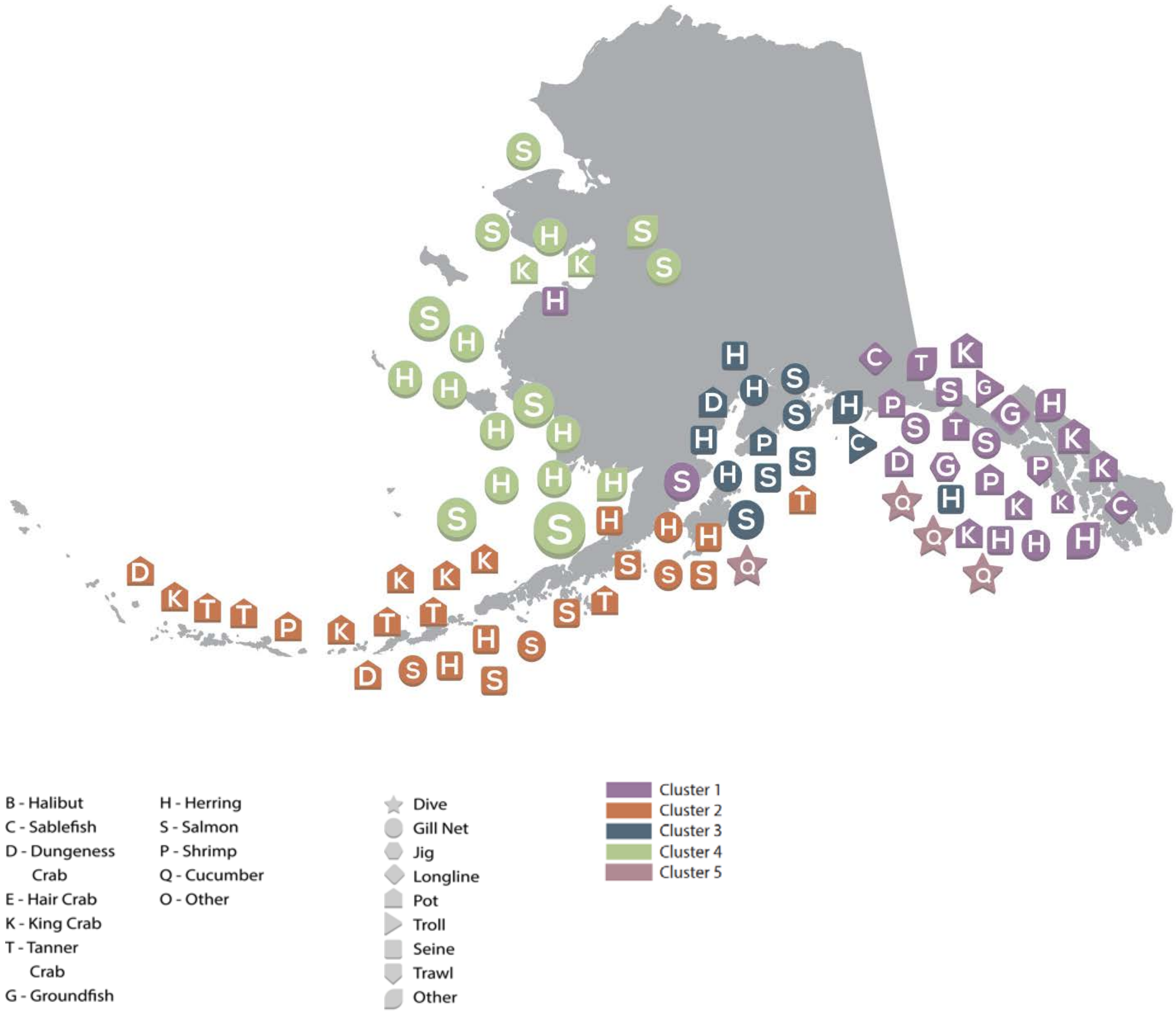
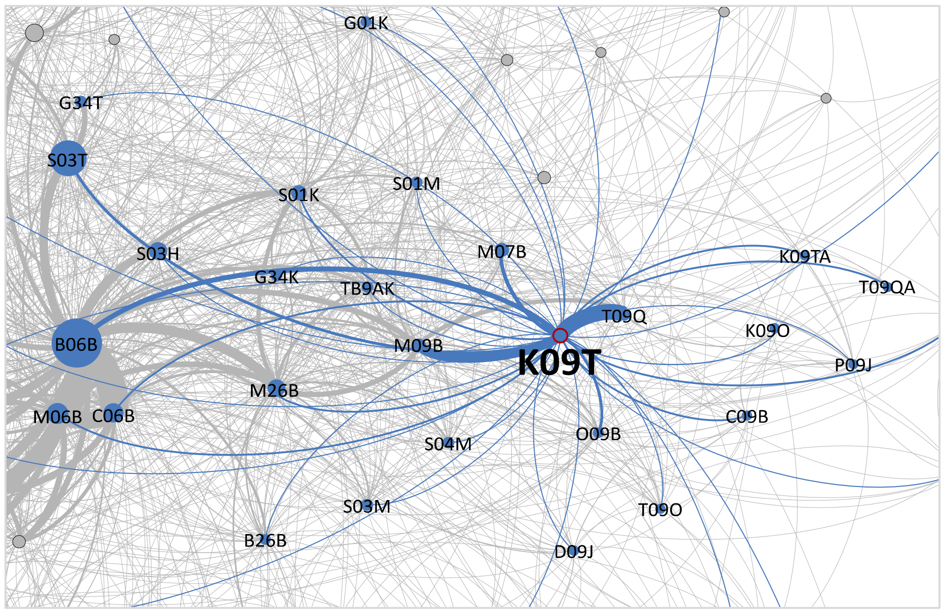


Figure 4: Bristol Bay King Crab Fishery 2004-5. Node size represents relative number of permits issued for the fishery. Edge weight represents number of permit holders jointly permitted in those two fisheries.
Note: Only nodes with five or more permit holders are shown. The edges between BBK and its connected fisheries have been magnified in order to facilitate visual analysis and thus do not scale to the gray edges not connected to BBK.

2004 (a)



Spillover (b)

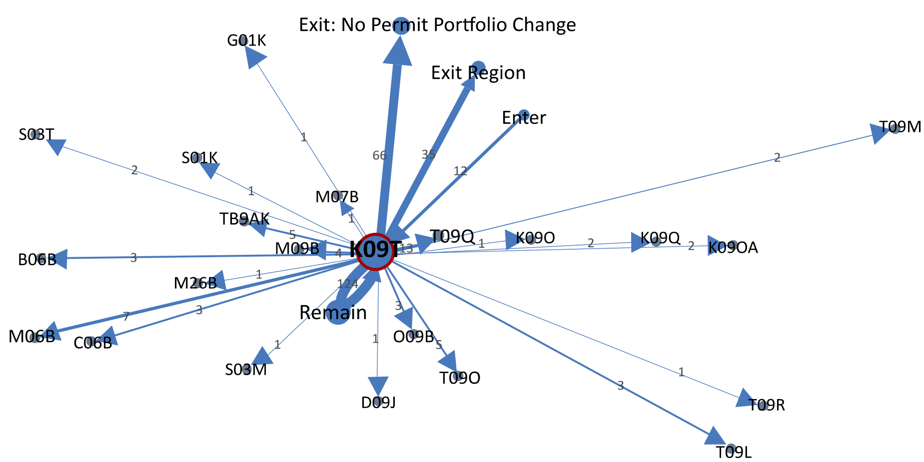


Figure 5: Flow of Permits in the Bristol Bay King Crab Pot Fishery (BBK), 2004-5: Following the implementation of the ITQ program, the following actions were taken by permit holders in the BBK fishery.
Note: The number of individual permit holders taking the action is in parentheses.

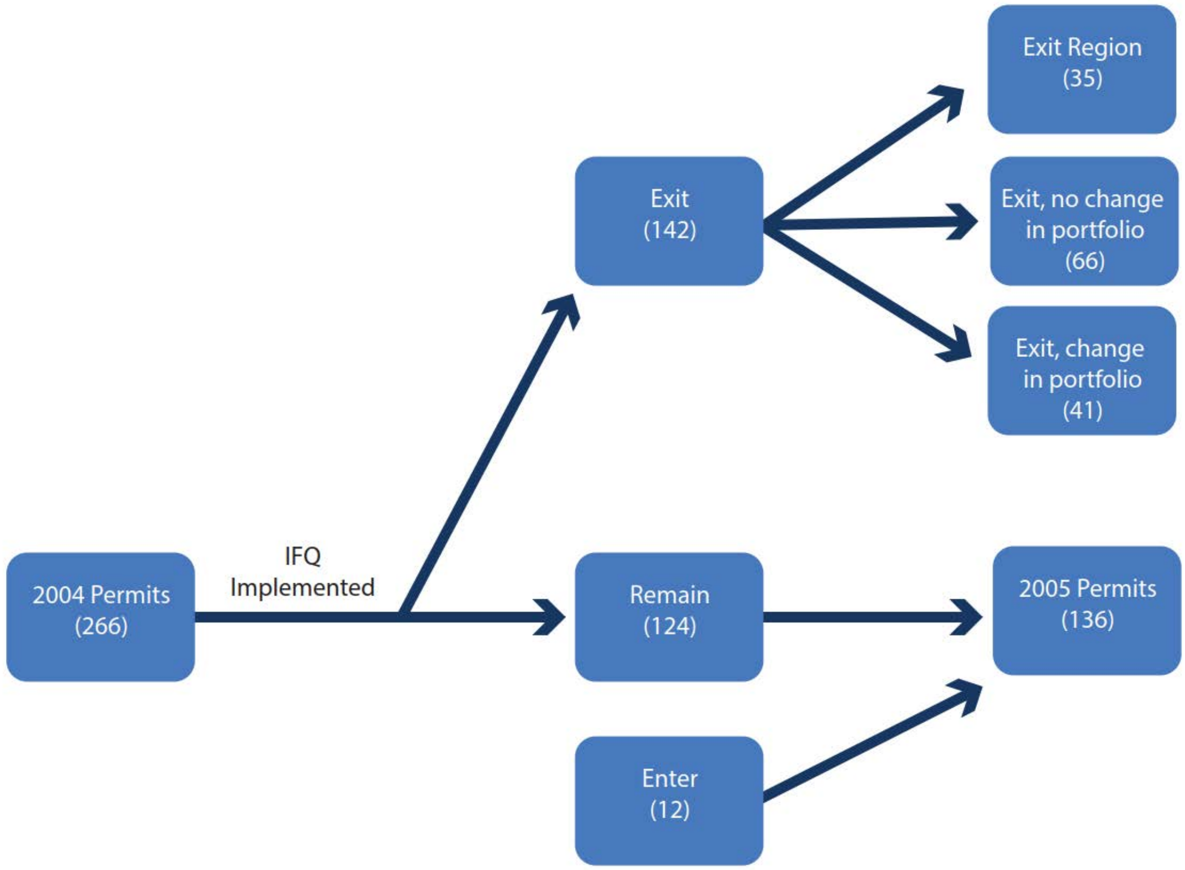


Table 1: Network Summary Statistics.

	Total Number of Fisheries	Fisheries Connected	Fisheries Unconnected	Density = Edges/ Potential Edges	Average Node Size	Average Edge Weight	Average Degree	Average Closeness Centrality
Entire Network	113	112	1	.32	177	5.82	35.29	.59
Fishing Region								
Statewide Only	22	22	0	.66	311	17.67	13.91	.77
Regional Only	91	90	1	.26	145	3.70	23.47	.55
Management Entity								
Federal Managed Only	10	10	0	.98	406	31.16	8.8	.98
State Managed Only	102	101	1	.29	156	3.72	29.35	.57

`

Table 2: Alaska Fishery (Node) Characteristics. Characteristics of fisheries for the statewide and regional fisheries with the highest closeness centrality.
Note: A list of characteristics of all 113 fisheries is available in the Appendix.

Fishery (gear-area-species code)	Federally Managed	Average Number of Permits	Degree	Average Edge Weight	Closeness Centrality	Cluster
Statewide (CFEC area code = B)						
Halibut – longline (B-6/61-B)	Y	2,261	106	34	0.96	1
Groundfish – longline (M-6/61-B)	Y	432	98	12	0.89	1
Sablefish – longline (C-6/61-B)	Y	625	85	18	0.80	1
Groundfish – jig (M-26-B)	N	404	80	9	0.78	2
Groundfish – pot (M-9/91-B)	Y	247	70	9	0.73	2
Salmon – troll (S-15-B)	N	961	67	16	0.71	1
Salmon – hand troll (S-5-B)	N	1,038	60	11	0.68	1
Halibut – jig (B-26-B)	N	53	51	2	0.65	2
Groundfish – hand troll (M-5-B)	N	57	51	1	0.65	1
Groundfish trawl (M-7/71-B)	Y	295	46	3	0.62	2
Regional						
Salmon – gill net – Bristol Bay (S-3-T)	N	1,844	93	7	0.86	4
Salmon – seine – Kodiak (S-1-K)	N	365	77	8	0.76	2
Salmon – seine – Southeast (S-1-A)	N	358	68	9	0.72	1
Sea Cucumber – Dive – Southeast (Q-11-A)	N	320	63	7	0.69	5
Shrimp – pot – Southeast (P-9/91-A)	N	273	63	9	0.69	1
Tanner Crab – pot – other (TB-9/91-AK)	N	175	62	8	0.69	2
Salmon – seine – AK Peninsula (S-1-M)	N	116	61	4	0.69	2
Roe herring – gill net – Norton Sound (G-34-Z)	N	260	60	3	0.68	4
Salmon – seine – Prince William Sound (S-1-E)	N	262	60	6	0.68	3
Dungeness Crab – pot – Southeast (D-9/91-A)	N	279	59	8	0.67	1

Table 3: Edge Properties. There are 1,994 undirected edges in the network, which represent 997 pairs of fisheries that shared at least one permit holder from 2006-2015. Aggregate network statistics appear in the first row. In the remaining rows, the edges are grouped by area and jurisdiction. There are two types of areas and two types of jurisdictions, so three combinations each of jurisdiction and area pairs (order of the pairing does not matter). The percentage of total edges falling into each area and jurisdiction category is given in parentheses.

	Number of Edges	**Potential Edges N*(N-1)/2**	**Average Edge Weight**
Entire Network	1,994	6,328	5.82
Fishing Region			
Statewide-Statewide	153 (8%)	231 (4%)	17.67
Regional-Regional	1,068 (54%)	4,095 (65%)	3.70
Statewide-Regional	773 (39%)	2,002 (32%)	6.40
Management Entity			
Federal-Federal	44 (2%)	45 (1%)	31.16
State-State	1,497 (75%)	5,151 (81%)	3.72
Federal-State	453 (23%)	1,177 (19%)	10.30

*Totals may not add to 100% due to rounding.

Table 4: Cluster Summary Statistics

Cluster	Nodes	Average Number of Permits per Fishery	Density	Average Degree	Average Edge Weight	Average Closeness Centrality	Most Central Cluster Fisheries
1	37	228	.63	22.60	12.50	0.75	Halibut, sablefish, and groundfish statewide longline
2	33	151	.58	18.67	5.25	0.72	Federally managed groundfish pot; statewide jig groundfish; statewide octopus/squid pot
3	15	59	.61	8.53	7.48	0.72	Southeast area fisheries. Top 4 are Prince William Sound: herring and shrimp pot; salmon seine and gillnet
4	21	282	.42	8.38	7.30	0.63	West and Northwest area fisheries.
5	5	103	1	4	15.25	1	Dive fisheries.
6	1	6	-	-	-	-	Scallop fishery, W22BV
7	1	13	-	-	-	-	Hair crab, E91QV

Table 5: Marginal effects of fishery characteristics on cluster membership

Characteristic	Probability of Sharing a Cluster[a] (a) Share Characteristic	(b) Do not Share Characteristic	Difference (a) - (b)	P-value
Species	0.232	0.254	-0.0219	0.162
	(0.0141)	(0.00633)	(0.0157)	
Gear	0.336	0.228	0.108	0.000
	(0.0146)	(0.00636)	(0.0162)	
Area	0.549	0.162	0.387	0.000
	(0.0150)	(0.00602)	(0.0162)	

[a]Average predicted probability from Logit regression model with standard errors in the parentheses.