Title: When does it pay to cooperate? Strategic information exchange in the harvest of common-pool fishery resources

Authors: Michele L. Barnes[a,b,c]*, Shawn Arita[d], Kolter Kalberg[b], and PingSun Leung[a]

Author Affiliations:

[a] Department of Natural Resources and Environmental Management, University of Hawaii at Manoa, 1910 East-West Rd., Sherman 101, Honolulu, HI 96822, USA; barnesm@hawaii.edu, psleung@hawaii.edu

[b] Joint Institute for Marine and Atmospheric Research, University of Hawaii at Manoa, 1000 Pope Rd., Marine Science Building 312, Honolulu, HI 96822, USA;
KK: kolter.kalberg@noaa.gov

[c] Australian Research Council Centre of Excellence for Coral Reef Studies, James Cook University, Townsville, QLD 4811, Australia; MB: Michele.Barnes@jcu.edu.au

[d] Economic Research Service, United States Department of Agriculture, 335 E Street SW, Washington, DC 20024, USA; SA: shawnarita@gmail.com

*Corresponding author
barnesm@hawaii.edu
Michele.Barnes@jcu.edu.au
+ 61 7 4781 6328

Abstract

Harvesting common-pool fishery resources is often a competitive activity and important questions remain about the costs and benefits of engaging in cooperative behavior. Here, we link comprehensive data on fisher's information exchange networks and economic productivity to test hypotheses about when it pays to cooperate by exchanging different types of strategic information. We find that being well connected locally in information exchange networks about both short-term topics (e.g., the location of species) and long-term topics (e.g., technical innovations) is positively associated with productivity in both the short-term (within fishing trips) and long-term (annually). In contrast, we find that exchanging both types of information across distinct social divides – a form of brokerage – is negatively associated with productivity. Our results therefore suggest that while there appears to be an economic benefit associated with cooperation across temporal scales in the harvest of common-pool fishery resources, exchanging strategic information across social divides may come at a cost – particularly under conditions of competition. We discuss our results in light of emerging research at the nexus of sociology and economics, providing key insight into the social-structural dynamics that help form the foundation for fisher decision-making and behavior.

Keywords: information exchange, cooperation, social network, fisher behavior, common-pool resources, fisheries

Acknowledgements

This project was funded by Cooperative Agreement NA11NMF4320128 between the Joint Institute for Marine and Atmospheric Research and the National Oceanic and Atmospheric Administration (NOAA). MB was also supported by National Science Foundation Social, Behavioral, and Economic Sciences Postdoctoral Fellowship Grant #1513354. We thank our interpreters, all of the fishers who participated in this project, and Joey Lecky for the development of Fig. 2. We also thank Steve Borgatti for technical advice. Data on catch and effort and fish sales was provided by the U.S. National Marine Fisheries Service Pacific Islands Fisheries Science Center, the National Marine Fisheries Service Pacific Islands Regional Office, and the Hawaii Division of Aquatic Resources. The views expressed herein are those of the authors and do not necessarily reflect the views of NOAA, the USDA, or any of its subdivisions.

1. Introduction

There is a large body of theoretical and empirical research that seeks to understand the conditions that facilitate cooperation in the harvest of common-pool resources. Classic economic theory would predict that individuals, acting as rational self-interested actors, would likely choose to defect from attempts at cooperative arrangements due to the nonexcludable and rivalrous nature of common-pool resources (Gordon, 1954; Hardin, 1968; Scott, 1955). Yet many argue this conceptualization is too simplistic, and under certain conditions common-pool resource users may choose to cooperate (Gintis, 2000; Ostrom, 1990); for example, when groups are small and coercion is possible (Olson, 1965), or when cooperation is reinforced by norms, ethical codes, and institutions (Ostrom, 2000).

Information exchange among marine fishers has long been a key focus of investigations into cooperation in common-pool resource settings (Evans and Weninger, 2014; Gatewood, 1984; Haynie et al., 2009; Pollnac and Carmo, 1980; Wilson, 1990). Fishers operate in a dynamic and complex ecological environment, often covering vast spatial scales across the open ocean where spatiotemporal dynamics can change in unpredictable ways (Wilson, 1990). Decision-making in this context can be further complicated by a complex array of socio-political and economic processes. For example, in the U.S. pelagic fishers operate under the jurisdiction of the U.S Magnuson-Stevens Act (NOAA, 2006), are subject to both U.S. environmental legislation and binding international conservation measures, and are governed by international fishery management organizations[1], regional fishery management councils, and the U.S. National Marine Fisheries Service. Adding a further layer of complexity, all commercial fishers are faced with fluctuating fish prices, market competition, and the dynamics of supply and demand in deciding when and where to land their catch (Béné, 1996; Salas and Gaertner, 2004). Marine fisheries are thus characterized by repetitive and competitive interactions among individual fishers who must determine the most strategic use of inputs over time and space to transform wild stocks of fish into catch. Fishers need to make these critical decisions while accommodating their activities to complex and uncertain market dynamics, socio-political processes, and the spatiotemporal fluctuations of the open ocean.

To cope with this complexity, fishers may choose to cooperate by exchanging information with others to improve their decision-making (Salas and Gaertner 2004). Engaging in information exchanges can potentially reduce time and effort spent searching for fish aggregations (Branch et al., 2006; Gatewood, 1984), and facilitate the diffusion of technological innovations capable of enhancing vessel efficiency (Gezelius, 2007). However,

[1] Formally referred to as “Regional Fishery Management Organizations”, though they are international in scope.

decisions to engage in information exchange may be tempered by the competitive nature of fishing (Acheson, 1975; Gezelius, 2007; Wilson, 1990). Indeed, the rational actor model suggests that fishers acting in their own self-interest are unlikely to cooperate by participating in information exchanges because such exchanges can increase the efficiency of others (Gordon, 1954; Hardin, 1968; Scott, 1955). Yet existing empirical work in marine fisheries suggests that information transfer among fishers is widespread, though it does vary depending on the size, structure, and diversity of fishing communities, the biology of the fish involved, and the type and value of the information exchanged (Barnes-Mauthe et al., 2013; Branch et al., 2006; Gezelius, 2007; Wilson, 1990).

One of the most common arguments put forth is that fishers are more likely to cooperate by exchanging information with others when it is economically beneficial for them to do so (Haynie et al., 2009). Yet existing research that seeks to quantify the relationship between information exchange and economic gains in marine fisheries largely rely on simulations and other models that lack explicit data on patterns of information exchange in fishing communities (Dreyfus-Leon and Gaertner, 2006; Haynie et al., 2009; Millischer et al., 2006).[2] When it actually pays for fishers to engage in cooperative information exchange behavior therefore remains an important empirical question. To this end, we employ comprehensive data on networks of information exchange, catch and effort, and economic cost-earnings among pelagic tuna fishers to contribute a better understanding of when it pays to cooperate in the harvest of common-pool fishery resources.

In line with the literature on the structural aspects of social capital (Borgatti et al., 2009; Burt, 2000; Lin, 1999), our empirical approach rests on the assumption that fishers' structural position in networks of fishery-related information exchange can affect their ability to *access* information that can improve their decision-making. The ability to access information flowing through networks of information exchange can be exceptionally critical when dealing with aggregated and highly migratory species such as schools of tuna (Salas and Gaertner, 2004). In this case, there are two types of information that can potentially influence fisher's productivity: (1) *short-term information*, such as information on the location of species that can influence fisher productivity within fishing trips, and (2) *long-term information*, such as information on technical innovations that can influence fisher productivity over a longer period of time (Barnes et al., 2016b; Gezelius, 2007; Mueller et al., 2008; Wilson, 1990).[3]

---

[2] One exception is Turner et al. (2014) who presented explicit information exchange network information on lobster fishers, yet was limited to analyzing *perceived* levels of fishing success rather than actual productivity. A final exception is Barnes et al. (2016b), which the analysis presented here builds on.

[3] These definitions are in line with Gezelius (2007). Wilson (1990) refers to short-term vs. long-term information as "fine-grained" vs. "coarse-grained", while fishers studied in Muller et al. (2008) distinguished between "right now" and "after-hours" information, which was similar in scope to the categories identified here.

To our knowledge there are no existing empirical studies examining the relationship between long-term information exchange and fisher economic outcomes, though existing research does provide insight into what we might expect regarding short-term information exchange. Specifically, fishers who work with others rather than alone and are prominently located within short-term information exchange networks (i.e., "network prominence", see Fig. 1) have been found to be more successful, particularly when targeting highly mobile species (Barnes et al., 2016b; Dreyfus-Leon and Gaertner, 2006; Mueller et al., 2008). Network prominence refers to how central or well-connected locally one is in a social network, which tends to be associated with increased access to information and resources (Borgatti et al., 1998; Freeman, 1979) and has been positively linked to economic productivity (Abbasi et al., 2011; Greve et al., 2010). By their very nature, information exchange networks comprise information channels that can reduce the amount of time and investment needed to gather and process information (Molina‐Morales and Martínez‐Fernández, 2009). They can also enable learning through close contact and intensive interaction, which can foster innovation (Conley and Udry, 2010; Rogers Everett, 1995). Well-connected, centrally located individuals in such networks thus tend to have increased opportunities to capitalize on these benefits while pursuing their goals. Building on this existing theoretical and empirical foundation, here we propose and test the following hypothesis:

H1: Being well connected locally (i.e., network prominence) in both short-term and long-term information exchange networks will be positively associated with productivity in both the short-run (within fishing trips) and long-run (annually).

Though we expect that in general, the ability to access both types of information can provide advantages that enable fishers to be more productive, there are important differences between the exchange of short-term and long-term information that require consideration. Most notably, short-term information can almost immediately, and visibly, increase fishing success, whereas the effects of long-term information are much less immediate and tangibly visible. For example, information on the location of high-value species can reduce search effort and increase high-value catch, thereby decreasing costs while increasing revenues. The time-scale at which this occurs is almost immediate, i.e., productivity is increased within fishing trips. Perhaps more importantly, fishers are highly aware of this (Gezelius, 2007), particularly when all vessels unload their catch at a central location. Short-term information in marine fisheries is therefore known to be highly guarded, often only exchanged within small groups of trusted individuals (Gezelius, 2007; Wilson, 1990). This reflects the competitive nature of fishing and the highly visible effects of short-term information on fisher productivity, which calls into question how fishers that bridge divides between groups in the structure of short-term information exchange networks may fare.

Crossing social divides can be considered a form of bridging or brokerage (see Fig. 1), which has strong support in the literature for producing competitive advantages that lead to economic gains (e.g., Abbasi et al., 2011; Burt, 1992; Burt, 2005; Tsai and Ghoshal, 1998). This is primarily because groups that are largely disconnected in social structures often possess heterogeneous knowledge and resources – thus, people who broker across these divides have the ability to gain access to, and control over diverse information and resources, thereby gaining a competitive advantage (Burt, 2005). However, recent research has highlighted the fact that there are inherent pressures associated with brokering roles that can place constraints on actors, and these constraints can actually have a negative effect on productivity (Bizzi, 2013; Krackhardt, 1999; Stovel and Shaw, 2012). For example, when social networks are clustered, and particularly in competitive environments, an "us-them" attitude can emerge (McPherson et al., 2001). Those who broker across distinct groups in such settings can face conflicting normative pressures. Others may also begin to question their loyalties and commitments, which can generate distrust from actors on both sides of the divide (Bailey, 1963; Stovel et al., 2011; Stovel and Shaw, 2012). Exploring this potential issue for the first time in an environmental system, Barnes et al. (2016b) recently found that fishers who bridge distinct social divides in short-term information exchange networks may actually face an economic penalty, i.e., they found that brokers generated significantly less revenue than your average fisher. In interpreting their findings, the authors suggest that because fishing is such a competitive activity, and because short-term information tends to only be exchanged within small groups of trusted individuals due to its ability to almost immediately and visibly affect productivity, brokers may be penalized for interacting across groups. Specifically, they suggest that critical information may be withheld from brokers, who might be seen as breaking normative rules of information exchange by cooperating with "the competition".

To our knowledge, there have been no empirical studies of the effects of long-term information exchange on fisher productivity. Though long-term information, such as technical knowledge on gear innovations, can similarly increase fishing success, the time-scale at which this occurs is typically longer, i.e., efficiency gains are typically realized over the course of multiple fishing trips, each of which can independently span several weeks. Perhaps more importantly, the effects of long-term information are less obvious. This helps to explain why long-term information is thought to be exchanged much more openly among fishers and across fishing communities than short-term information (Gezelius, 2007; Wilson, 1990). Existing research also suggest that fishers may be more open to exchanging technical and other long-term information because it can afford them with prestige by providing an opportunity to demonstrate a technical advantage (Gezelius, 2007). Thus, in addition to our expectation that being prominently located in long-term information exchange networks will be beneficial, we expect that the classically positive effects of brokerage are also likely to be realized. Specifically, we propose and test the following specific hypothesis:

H2: Brokering between distinct social divides (i.e., brokerage) in short-term information exchange networks will be negatively associated with productivity in the short-run (within fishing trips), yet brokering between social divides in long-term information exchange networks will be positively related with productivity in the long-run (annually).

In summary, we extend previous enquires into the effects of information exchange among fishers by leveraging explicit information exchange network data on both short-term and long-term topics among a population of fishers. Though we expect that cooperating by exchanging information will generally be associated with economic benefits via increased productivity to individual fishers, we hypothesize that these benefits will differ to some extent depending on the type of information exchanged: short-term vs. long-term, which are temporally tied to when we expect to see these effects on productivity.

The remainder of this paper is structured as follows. In section 2 we describe the context of our study system. Section 3 provides a detailed description of our data, methodological approach, and empirical model. In section 4 we present our results. In section 5 we discuss our results and the limitations of the data, and conclude with implications for fisheries management and recommendations for future research.

2. Study System: Hawaii's Longline Fishery

Hawaii's pelagic longline fishery (Fig. 2) is a multimillion-dollar industry that supplies local and international markets with fresh tuna, swordfish, and other pelagic fish. In 2012 there were 129 active vessels that generated approximately USD $94 million in revenue over the course of 19,424 fishing sets on 1,437 trips (see: http://www.pifsc.noaa.gov/fmb/reports.php). Tuna, primarily bigeye (*Thunnus obesus*) is targeted with continuous mainlines that hang 2,000 - 3,000 baited hooks on dropping intervals strung between a procession of floats at depths of approximately 40 - 400 meters over a range of 25 - 45 nautical miles in the open ocean. A small portion of the fleet also targets swordfish (*Xiphias gladius*) for a portion of the year using shallow-set mainlines hanging approximately 700 - 1,000 baited hooks at depths of approximately 30 - 90 meters.

Hawaii's longline fishers are restricted from fishing within 50 - 75 nautical miles of Hawaii's coastline, and tend to fish both within and outside of the U.S. Exclusive Economic Zone bordering the Hawaiian Islands and in both the western and central Pacific ocean and eastern Pacific ocean.

Though Hawaii has a diverse multicultural background (Nordyke, 1989), the fishery is made up of only three distinct ethnic groups: a group of Vietnamese-Americans, Euro-Americans, and Korean-Americans; and communication among fishers is significantly more extensive within ethnic groups than between groups (Barnes-Mauthe et al., 2013; Barnes-Mauthe et al., 2014). In social network terms, this is an example of a homophily effect, i.e., "birds of a feather flock together" (McPhersan et al. 2001). In this case, the homophily effect has a substantial impact on the overall structure of fisher's information exchange networks, and low levels of trust across groups have been documented (Barnes-Mauthe et al., 2013; Barnes-Mauthe et al., 2014).[4]

3. Methods

3.1 Data

To assess the role of having access to different types of information on fisher productivity we utilized data on fisher's information-exchange networks, annual and trip-level expenditures, and fish sales. These data are described in turn.

3.1.1 Information Exchange Networks

Comprehensive data on information exchange among more than 90% of all Hawaii longline fishers (n = 143)[5] was collected via a structured survey by Barnes-Mauthe et al. (2013) between May 2011 – January 2012. By fishers, we mean vessel owners and operators, which include both hired captains and owners who also operate their vessel, i.e., 'owner-operators'. In the survey, respondents were asked to identify up to 10 individuals they commonly exchanged useful information with regarding different aspects of fishing. Thus, the relationships identified represent respondent's perceptions of two-way information sharing ties. Though it could be argued that asking fishers to separately identify people they gave useful information to and people they got useful information from would have been more fruitful for identifying information access advantages, doing so would have doubled the

[4] Existing quantitative and qualitative research strongly suggests that ethnicity plays the dominant role in influencing the network homophily effect and the overall structure of Hawaii's longline fishery information exchange network over all other fisher attributes, such as age, title, education, and experience (Barnes-Mauthe et al., 2013).

[5] The original dataset included 145 respondents, two of which were dropped due to incomplete information.

time it took fishers to complete the survey. Because Hawaii's longline fishers typically operate year-round, only coming to port for an average of 1-4 days when unloading catch and restocking before their next trip, such a substantial increase in respondent burden would have dramatically reduced our sample size. In addition, discussions with key informants from each ethnic group prior to conducting fieldwork suggested gauging what respondents considered to be two-way information exchange relationships would be more likely to reduce bias in the sample. This was due to the expectation that fishers would have been prone to overestimating their importance for sharing useful information with others, while underestimating the level at which they relied on others for useful information. In this case, asking fishers to report who they exchanged information with was therefore selected as the most appropriate approach.

After nominating individuals considered useful for information exchange, respondents were asked to disclose which topic(s) were discussed with each individual from a predetermined list. The topics included covered aspects of fishing that were determined through discussions with key informants as important for decision making in either the short-run or long-run, i.e., they could be considered either short-term or long-term topics. Short-term topics included (1) fish activity (i.e., "what the fish are doing"), (2) site catch/set location (where the fish are), (3) bycatch (which is preferably avoided while at sea), and (4) weather. Long-term topics included (1) vessel technology, (2) hiring of captain or crew, (3) fishery regulations, and (4) gear maintenance. Respondents often nominated other fishers as important for information exchange, though some industry leaders[6] and government/management officials were also identified. The survey also collected basic socio-demographic information from respondents, and was fielded in person with the help of Vietnamese and Korean translators, as needed.

Using this data, we identified two different networks of information exchange. The first network included ties used to exchange short-term information. Discussed in detail in the following sections, we employ this network in our analysis of short-run, or trip-level productivity for all vessel operators, including both hired captains and vessel owners who also captain their vessel (owner-operators). The second network included ties used to exchange long-term information. Discussed in detail in the following sections, we use this network in our analysis of long-run, or annual productivity for all vessel owners (also

[6] The definition of "industry leader" was adopted from Barnes et al. (2013) who relied on key informants to define industry leaders as those whose role in the fishery included one or more of the following: (a) current or past representative on fishing association boards or fishery management councils relevant to Hawaii's longline fishery; (b) high-level, prominent employee or associate of a fishing organization, the Hawaii Fish Auction (where the majority of fish caught by Hawaii's longline fleet is landed), or other group that supports operations of Hawaii's longline fleet; (c) owner or high-level, prominent employee of supply stores that support Hawaii longline operations."

including owner-operators). In this fishery less than 25% of the population both owns and operates their vessel; the remainder of vessel owners rely on hired captains (Barnes-Mauthe et al., 2013). The two networks are presented in Fig. 3.

3.1.2 Annual and Trip-Level Expenditures

In collaboration with NOAA's Pacific Islands Fisheries Science Center (PIFSC) Economics Program (see Kalberg and Pan, forthcoming), we collected information on vessel operating costs incurred during the 2012 calendar year from vessel owners and operators through the use of a structured survey. The survey focused primarily on annual fixed costs, and was fielded in person from January – September 2013 with the help of Vietnamese and Korean translators.

All trips targeting swordfish and 20% of trips targeting tuna that originate in Hawaii are federally mandated to carry an onboard fishery observer that collects detailed data on catch and effort. Through a joint effort between the PIFSC Economics Program and the Pacific Islands Regional Office (PIRO) Observer Program (Pan et al., 2014), vessel operators of all federally observed trips are also asked to voluntarily provide trip-level variable costs. Trip-level expenditures were voluntarily provided through this mechanism on 60% of all observed trips in 2012. Using this sample, we developed a regression model to estimate a trip cost function accounting for individual vessel and trip characteristics; such as vessel length, number of fishing sets, trip length, and travel distance; in order to generate cost information for all trips for which we did not have expenditure information. In the example of fuel cost estimation for a particular trip, the fuel usage is estimated based on its trip length (days), travel distance (miles), vessel size (feet), and a dummy variable to represent an individual vessel's unobservable heterogeneity (see Kalberg and Pan, forthcoming).

3.1.3 Fish Sales

The Hawaii Department of Aquatic Resources maintains detailed records of fish purchased from Hawaii's longline fleet by Hawaii marine fish dealers, including information on number of fish bought by species, price per pound paid, and weight and value of each fish. By linking these dealer reports with fisher's federally mandated logbook records we directly acquired revenue data for all longline trips that landed their catch in Hawaii in 2012. There were also a handful of Hawaii-based trips that landed their catch outside of Hawaii in 2012, resulting in a record of catch and effort present in logbooks, but not accounted for in the dealer reports. As a proxy revenue for these trips, the average weekly fish prices and average weight by species from the dealer data were multiplied by the number of kept fish by species as recorded in federal logbooks to estimate trip revenues. Weekly average prices and weights were used to mitigate the variation a single vessel might influence in daily averages, while still maintaining the temporal variation in both price and weight per piece of fish kept (see Kalberg and Pan, forthcoming).[7]

3.1.4 Data Compilation

We integrated all data on expenditures and sales using vessel permit numbers or vessel names and landing dates, trip return dates, and sales data. We used information on vessel ownership during the 2012 calendar year collected via the information exchange network survey to link vessel owners to their respective vessels. Vessel operators were linked to each fishing trip using a combination of fishery observer data that included operator names, and information from the network survey, where vessel operators reported all vessels they had operated within the last five years. In accordance with strict confidentiality agreements, the data was stripped of all names and other personally identifying information immediately after the data was merged.

3.2 The Production Function Model

Following similar approaches in the literature (e.g. Fafchamps and Minten, 2002), we incorporate information exchange proxies as added inputs in the production function in order to test the role of information exchange on fishers' economic productivity. The general production function can be written as,

$$Y = F(L, K) \tag{1}$$

where total production *Y* is assumed to be a function of labor *L* and capital *K*. Following Fafchamps and Minten (2002), in specifying a production function for Hawaii's longline fishers we can distinguish physical from human capital and include information exchange inputs as an additional factor of production. Consider a fishing vessel with economic outcome *Y* (revenue), labor *L* (crew size), capital or inputs *K* (trip length, fixed costs, variable costs, and other inputs), human capital *H* (education, experience), information exchange inputs *I* (network prominence, brokerage), and vessel and owner/operator specific characteristics *Z* (vessel size, vessel age, target species, ethnicity, etc.). Equation 1 can therefore be re-specified as,

$$Y = F(L, K, H, I, Z) \tag{2}$$

[7] Average auction prices for the same species can vary significantly between vessels due to fishing grounds, fish handling practices, the average time between landings and sales. There can also be substantial variations in fish size due to spatial-temporal variations.

Here, we are specifically interested in information exchange, *I*. If information exchange is irrelevant to fisher's productivity, *I* should have no effect on output when controlling for *L*, *K*, *H*, and *Z*. Yet we hypothesize that when accounting for the other factors of production, being well connected locally in information exchange networks, i.e., network prominence I_p, will have a positive effect on *Y*, while brokering between socialy distinct groups, I_b will have a negative effect for vessel operators in the short-run, but a positive effect for vessel owners in the long-run. Our empirical model following the traditional log-log functional form is therefore specified as,

$$\ln(Y) = \beta_0 + a_1 \ln(L) + \sum_{n=1}^{N} a_n \ln(K_n) + \beta_1 H_{ed} + \beta_2 \ln\left(H_{exp}\right) + \beta_3 \ln\left(I_p\right) + \beta_4 \ln(I_b) + \sum_{n=1}^{N} \beta_n Z_n \quad (3)$$

where *Y* denotes gross revenue, *L* represents crew size, *K* corresponds to various capital inputs described in Table 1, H_{ed} is a dummy variable for education (some college or higher), H_{exp} denotes years of fishing experience, *I* are the same as described above, and *Z* denotes various vessel and operator specific variables (see Table 1).

Described in both Pradhan et al. (2003) and Barnes et al (2016b), using gross revenue instead of a quantity as the output is not truly a production function. However, catches in Hawaii's longline fishery typically feature multiple species that receive different market prices (i.e., vessels operate as multi-product firms). The use of value as an output rather than aggregated quantity of fish landed is therefore standard practice.[8]

Using this empirical approach, we estimated two separate production functions: one for vessel owners assessing the role of information exchange about long-term topics at the annual level (the long-run), and one for vessel operators assessing the role of information exchange about short-term topics at the trip-level (the short-run). Because the network metrics used to capture information exchange can violate the assumption of independence central to standard statistical approaches, we applied a nonparametric bootstrap method to estimate robust standard errors following Banerjee et al. (2013). Both analyses correspond to the 2012 calendar year.

3.3 Information Exchange Metrics

[8] The value output is indicative of both quantity of production and the quality of the product. Tuna quality is largely a factor of trip length, fishing grounds and fish handling practices.

To gauge information exchange, we employed structural measures of network prominence and brokerage using the information exchange networks described in section 3.1.1 (see Table 1). To capture network prominence we used indegree centrality. Indegree centrality is a simple measure of local centrality that measures the number of incoming edges (i.e., ties) a node has in a network. We used indegree centrality rather than outdegree (ties going out from an actor) because we assume incoming ties more accurately represent fishers' ability to access information in this case due to an underlying level of trust associated with being nominated by others as someone they commonly exchange information with. Outdegree was also capped in our survey at a max of 10, i.e., fishers were only asked to nominate up to 10 individuals. The variation of outdegree was thus limited to between 0 and 10, which constrained its ability to identify truly well-connected fishers who had access to more than 10 information sources. By comparison, indegree ranged from 0 to 23 for vessel operators in the short-term information exchange network, and from 0 to 50 for vessel owners in the long-term information exchange network, suggesting that at least some fishers indeed have the ability to access information from more than 10 independent sources when needed.

We measured brokerage using both a structural and qualitative approach. Structural measures of brokerage capture bridging or brokering across groups that are structurally distinct in a social network, while qualitative measures capture bridging or brokering across socially heterogeneous groups (Borgatti et al., 1998). To capture structural brokerage across otherwise disconnected groups, we employed the measure network 'efficiency', which builds on Burt's (1992) theory of structural holes. In his discussion of structural holes, Burt (1992) was primarily interested in the number of opportunities for brokerage in a network. Building on this, the efficiency measure captures the suitability of a network for brokerage, given the number of opportunities, by idealizing non-redundant contacts. More formally, efficiency calculates the number of disjoint groups an actor is connected to divided by their total number of contacts, where disjoint groups are those that are otherwise not connected.[9] Due to the strong social divides along ethnic lines present in Hawaii's longline fishery (Barnes-Mauthe et al., 2013; Barnes-Mauthe et al., 2014), we also conceptualized brokerage qualitatively as the total number of ties each actor had that spanned ethnic groups. This measure was inspired by existing work that argues ties that bridge heterogeneous subgroups in networks constitute an important form of brokerage (Borgatti et al., 1998; Stovel and Shaw, 2012), and was modeled after Barnes et al. (2016b).

We generated indegree centrality and brokerage metrics using two separate networks for vessel owners and operators (Fig. 3). For vessel owners, we used the long-term network

[9] Efficiency calculates the effective size of an actor's ego network divided by their degree centrality, where effective size equals degree centrality minus the average degree of alters (see Abbasi et al., 2014).

described in section 3.1.1 which consisted of ties identified by all respondents as important for exchanging information about *vessel technology*, *hiring captain or crew*, *gear maintenance*, and *fishing regulations*. In the network survey, respondents were asked how valuable the information was that they exchanged with each person they nominated (very valuable, somewhat valuable, not valuable). Because we were interested in information that could, in theory, boost fisher productivity, ties deemed "not valuable" were dropped. The remaining information exchange network was treated as binary, i.e., it included all ties reported as very valuable or somewhat valuable by respondents. There were two sets of partner owners in our data who jointly shared multiple vessels. We treated partner owners as a single actor by merging their ties. Specifically, if a set of partners each identified a tie to the same person, we counted this as one outgoing tie for the partner pair. Likewise, if a different actor identified a tie to both individuals in the partner pair, we treated this as one incoming tie. The resulting network includes 167 nodes, 781 ties, has a mean geodesic distance of 4.17, an average indegree of 4.73 ties, one weakly connected component containing all nodes, and a homophily index of -0.86, where -1 indicates extreme ethnic homophily[10] (Fig. 3). Of the 167 nodes, 153 were fishers. Of the remaining nodes, 10 were industry leaders not directly involved in fishing (i.e., they did not own a fishing vessel) and four represented government or management officials that respondents deemed important for information exchange.

For vessel operators, we used the short-term network described in section 3.1.1 which consisted of ties identified by all respondents as important for exchanging information about *fish activity*, *site catch/set location*, *bycatch*, and *weather*. As in the long-run network, ties identified as "not valuable" were dropped. The remaining information exchange network was treated as binary, i.e., it included all ties respondents reported as very valuable or somewhat valuable. The resulting network included 158 nodes, 620 ties, a mean geodesic distance of 4.12, an average indegree of 3.92, one weakly connected component containing all nodes, and a homophily index of -0.88 (Fig. 3). Of the 158 nodes, 150 were fishers and eight were industry leaders deemed important by respondents for information exchange. With the exception of a single captain, everyone in the vessel operator short-term information exchange network appears in the vessel owner long-term information exchange network. In contrast, the vessel owner long-term information exchange network has seven owners, one captain, one owner-operator, six industry leaders, and six government or management officials who do not appear in the vessel operator short-term information exchange network.

[10] The homophily index is equal to the number of ties external to groups minus the number of ties internal to groups, divided by the total number of ties possible. This results in a value that ranges from +1 (in cases of extreme heterophily) to -1 (in cases of extreme homophily).

3.4 Other Inputs

Other inputs used in the production function are presented in Table 1. Explanatory variables for vessel owner's annual-level production function differed slightly from that of vessel operator's trip-level production function, primarily due to the difference in scale at which the production process was estimated (see Tables 2 and 3). Specifically, vessel owner's production functions were estimated at the annual level accounting for all trip days, inputs, and total annual revenue, whereas operator's production functions were estimated at the trip level accounting for trip days, average inputs, and average trip-level revenue. For vessel owners, capital inputs were aggregated into fixed and variable costs, where the former included costs associated with dry docking, engine work, gear added/replaced, and continuous maintenance; and the latter included trip-level costs, such as fuel, bait, engine oil, provisions, ice, fishing gear replacement, and communication. Only trip-level costs were included in operator's production functions (denoted as *other inputs*, Table 1). Vessel and operator specific variables are also included, one of which accounts for fishers that both own and operate their vessel.

3.5 Sample

The compiled data described in Section 3.1.4 included information on 128 unique vessels, 30 of which were associated with owners not present in the network dataset. Data on an additional seven vessels were missing key productivity variables, resulting in a total usable sample of 91 vessels associated with 87 owners to be used to estimate vessel owner's annual-level production function. 15% of these vessels targeted swordfish for at least one trip during the year, while the other 85% targeted tuna only. Summary statistics for the 2012 annual-level data included in vessel owner's production function are presented in Table 2.

For vessel operator's trip-level production function, we first evaluated swordfish trips separately from tuna trips because they consist of very different fishing profiles (i.e., different depths, times, number of hooks, etc.). The trip-level data for 2012 included 984 recorded tuna trips, 40 of which were taken by operators not present in the network data. An additional 91 trips were missing key variables, resulting in a total usable sample of 853 tuna trips taken by 84 vessel operators on 85 unique vessels during the 2012 calendar year. The 2012 trip-level data also included a total of 54 recorded swordfish trips made by 14 unique vessels. However, operators of these vessels were all Vietnamese-American, and there was very little variation in their patterns of information exchange or vessel operating characteristics. Our analysis on vessel operators therefore focuses on tuna targeting trips only. Note that all vessel operators on swordfish trips also participated in tuna trips during the 2012 calendar year. Summary statistics for the trip-level data included in vessel operator's production function are presented in Table 3.

4. Results

Our initial estimation of vessel owner's annual-level production function described in Eq. 3 exhibited problematic signs of collinearity among the information exchange metrics.[11] Specifically, we found that inter-ethnic ties had a strong positive correlation with both indegree centrality and efficiency for vessel owners in the long-term information exchange network (Table 4). The same relationship was not present among vessel operators in the short-term information exchange network (Table 4). We therefore had to exclude inter-ethnic ties in the final long-run model for vessel owners, yet were able to retain it in the short-run model for vessel operators, where there were no problematic signs of multicollinearity.[12] Thus, in our analysis of the relationship between long-term information exchange and vessel owner productivity, brokerage is restricted to the structural measure *efficiency*, and direct inferences about the potential effect of the qualitative measure *inter-ethnic ties* cannot be made. Final results for both production functions by ordinary least squares are presented in Table 5.

In support of our first hypothesis, our results show that being well connected locally (i.e., indegree centrality) in both short and long-term information exchange networks has a significant, positive relationship with productivity for both vessel operators at the trip-level and vessel owners at the annual level. The effect is stronger for vessel owners ($\beta = 0.085$, $p < 0.05$ vs. $\beta = 0.050$, $p < 0.10$) but not statistically significant in terms of the difference. Results regarding brokerage are partly at odds with our second hypothesis. We expected bridging both structurally and socially distinct groups in the short-term information exchange network to be negatively associated with productivity for vessel operators in the short-run, and our results lend support to this hypothesis. However, we expected the opposite to be true for vessel owners in the long-run, yet what we find instead is that structural brokerage (efficiency) also has a significant, negative relationship with productivity for vessel owners in the long-run (Table 5).

Results regarding other inputs are largely in accordance with expectations. All capital variables have the expected sign, though only trip days and trip-level capital inputs are significant (Table 5). Results regarding human capital are mixed, with experience playing a

[11] The mean variance inflation factor (VIF) was 3.06, and VIFs for inter-ethnic ties and centrality were both > 3.
[12] The mean VIF is 2.14, and the VIF for all short-run information exchange metrics are < 1.5.

positive yet insignificant role, and education having a strong negative relationship with productivity in both the short-run and long-run. Fishers operating older vessels perform less well both in the short-run and long-run. Vessel size is also important, and in this case temporal scale matters. Specifically, medium sized vessels generate significantly more revenue on average than larger vessels in the short-run, yet having a larger vessel is positively associated with productivity in the long-run – though this relationship is not statistically significant. Our results also indicate that owners who switch between fishing for swordfish and tuna throughout the year are significantly less productive. Both owning and operating your vessel does not appear to play a significant role in influencing revenue in either case. Our results also indicate that when controlling for other variables, Euro-American fishers (both owners and operators) generate significantly more revenue than others.

5. Discussion and Conclusion

Our results offer evidence that engaging in strategic information exchange about both short-term and long-term topics with close, localized contacts is positively related to economic productivity for commercial fishers (see results on network prominence, Table 5). These findings extend the results of Barnes et al. (2016b) to account for long-term information exchange and add further empirical support to broader claims on the value of cooperation in the harvest of common-pool fishery resources (Dreyfus-Leon and Gaertner, 2006; Millischer et al., 2006; Mueller et al., 2008; Turner et al., 2014; Wilson, 1990). Though a direct positive association between social interaction and performance has also been documented in other fields (e.g., Tsai and Ghoshal, 1998), to our knowledge no existing study has jointly examined this association in relation to both short-run and long-run performance in the same setting.

The message here appears relatively simple – the more direct contacts fishers have access to that they can leverage strategic information from on both short-term and long-term topics when needed, the better they perform in harvesting target species. This relationship holds in both the short-run (i.e., within fishing trips) and long-run. However, it's important to note that there is likely a limit to the positive relationship between the number of information exchange contacts that fishers have direct access to and higher returns because of saturation: as the number of information exchange contacts among fishers increases, the information exchange network as a whole becomes hyperconnected, likely resulting in information being redundant, rather than novel (Bodin and Crona, 2009). Another important caveat is that fishery resources are rivalrous in nature, and Hawaii's longline fishers operate under a total allowable catch on bigeye tuna that applies to the entire fishery. This implies that if maximizing centrality in information exchange networks has a direct casual relationship with productivity, it's unlikely that this relationship would hold as more fishers sought to maximize their centrality. This is due to the simple fact that there's a limit to how much can be caught.

In contrast to our results regarding strategic information exchange with close, localized contacts, we found that engaging in information exchange across structurally or socially distinct divides (brokering) may come at a cost. The most interesting result is that when it comes to bridging structural divides, the type of information exchange does not seem to matter – brokering has a negative association with productivity whether the information exchanged is about long-term topics such as technological innovations, or short-term topics thought to be more highly guarded, such as the location of fish aggregations. This stands in contrast to dominant theories regarding brokerage that argue for its ability to provide tangible economic benefits (e.g., Abbasi et al., 2011; Burt, 1992; Burt, 2005; Tsai and Ghoshal, 1998), and is somewhat puzzling considering existing research in fisheries examining cooperative information exchange behaviors. For example, Mueller et al. (2008) found that highly successful fishers in the Great Lakes area generally exchanged fishing related information more frequently and with more individuals both within *and outside* their subgroup[13] than less successful fishers. They also found that information exchanges *between* subgroups (i.e., brokerage exchanges), tended to be more reliable than within, which implies brokerage would likely have been even more important for fisher success in their case. Moreover, long-term information is thought to be much more commonly exchanged across fishing communities than short-term information (Gezelius, 2007; Wilson, 1990). Indeed, even in our case we found a higher level of ties crossing both social and structural divides in the long-term information exchange network than in the short-term information exchange network (Tables 2 and 3). Intuitively, one would expect that fishers perceive a benefit from these brokerage relationships, yet our results clearly indicate they are associated with a measurable economic disadvantage.

Though our findings regarding brokerage were somewhat unexpected and diverge from dominant theories (i.e., Burt, 1992), the overwhelming majority of existing empirical work on brokerage has been conducted in corporate and organizational settings comprised of socially homogenous populations, and contrary evidence in more diverse environments has been emerging. For example, Xiao and Tsui (2007) found evidence that the benefits of brokerage typically found in more individualistic cultures can actually be reversed in cultures

[13] Subgroup is a network term used to describe individuals that are more densely connected to eachother than others in the network, thus, exchanges between them is a form of brokerage.

where working collectively is considered important. The potential drawbacks of brokerage have also been highlighted by Bizzi (2013), who showed that group composition can sometimes constrain individuals, having a negative impact on their performance. Additional research in sociology provides even further insight into our puzzling result, particularly when considering the competitive nature of fisheries. In line with identity theory (Tajfel and Turner, 1979) and role conflict (Goffman, 1959), diverse settings characterized by strong homophily and fragmentation can result in strong group identities. In cases where strong (and potentially conflicting) social identities exist, which can be related to cultural background or other, more subtle distinctions, the behavior of individuals is often heavily influenced by peer pressure and normative expectations (Krackhardt, 1999). Sometimes these identities cause individuals to emphasize their differences with others, which can decrease trust, amplify conflict (Baerveldt et al. 2004), and result in discriminatory behavior across groups (Tajfel and Turner, 1979) – particularly under conditions of competition (Poteete and Ostrom, 2004). Thus, in certain contexts brokering can be more tenuous and constraining for individuals (Bizzi, 2013; Stovel et al., 2011), making it more difficult for them to realize the information access advantages that are typically associated with bridging across distinct social groups (Podolny and Baron, 1997). Indeed, recent research suggests that in complex, dynamic environments, brokering between disparate parts of a social network can result in *disadvantaged* access to information (Aral and Van Alstyne, 2011). It is well recognized that marine fisheries constitute complex, dynamic systems (Jentoft, 2007; Levin and Lubchenco, 2008; Wilson, 1990), and our results suggest that when this is coupled with competition, exchanging strategic information across distinct social divides is associated with a demonstrable economic cost.

In the case of Hawaii's longline fishery, it's possible there exists a common suspicion of fishers interacting across strong social divides driven by a lack of trust, which can result in brokers being penalized by other fishers (Barnes et al., 2016b). For example, specific strategic information that could knowingly increase fishing efficiency may simply be withheld from brokers. A general sentiment of mistrust across distinct groups, particularly ethnic groups, in this fishery has indeed been repeatedly observed by field researchers, leading to it being characterized as ethnically fragmented despite the ties that exist across groups (Barnes et al., 2016b; Barnes-Mauthe et al., 2013; Barnes-Mauthe et al., 2014). Ethnic fragmentation has been shown to negatively impact trust, cooperation, and the provision of public goods (Alesina et al., 2014; Alesina and La Ferrara, 2002; Chakravarty and Fonseca, 2014; Pomeroy et al., 2007), though histories and other factors can mediate these relationships (Varughese and Ostrom, 2001).

Our results leave us with a lingering question: if brokers are experiencing an economic disadvantage for bridging distinct social divides, then why do they broker? Aside from the simple explanation that fishers may be unaware of the economic disadvantage associated with brokerage, it's possible that brokering provides fishers with other, non-monetary rewards, such as benefits to their reputation and standing in the community (Gezelius, 2007). We suspect this might especially be the case for vessel owners exchanging information about fishery management, technological innovations, and other long-term topics, as previous accounts of fishers in other settings suggest engaging in this sort of information exchange is thought to increase social prestige (Gezelius, 2007). Still, whether brokerage provides non-monetary benefits of value to fishers remains an open question that could be investigated in future research. The cross-sectional nature of our information exchange network data also prevented us from investigating how stable these brokerage relationships are. Considering brokerage is critical to achieve cooperation and collaboration across stakeholder communities, which has been linked with improved management of common-pool resources (Gruber, 2010; Nkhata et al., 2008; Ostrom, 1990), understanding how brokerage affects individuals and learning how to stabilize brokerage are key (Stovel et al., 2011), and could form the foundation for a fruitful future research agenda.

Our results are subject to some limitations, particularly the potential for endogeneity in our empirical models. One possible issue is that more successful fishers may have abilities, expertise, and other idiosyncratic features that set them apart from others that may also be related to their position in the information exchange networks. Acknowledging this possibility, we took several steps to minimize potential endogeneity. First, we asked fishers to specifically identify people with whom they exchanged useful information about fishing, rather than using second-hand data on formal group associations or spatial data on vessel movements assumed to represent cooperation. Second, we included a number of individual-level covariates (e.g., experience, education, owning and operating a vessel) that we know are important for explaining fisher productivity and individual level network characteristics in Hawaii's longline fishery, such as prominence and brokerage (see Barnes-Mauthe et al., 2014; Pradhan et al., 2003).

Still, there is the possibility of reverse causality. Instead of being centrally located in networks of information exchange improving fisher productivity, it may be the case that successful fishers are sought out more so than others for their skills and knowledge, driving the positive association between productivity and network prominence. Likewise, our finding of fisher's productivity being negatively associated with brokerage could be due to less productive fishers seeking out other fishers outside their ethnic group to compensate for their lower ability. Furthermore, the possibility of 'fluidness' of network positions sets forth complicated dynamic relationships between productivity and networks of information exchange (Reagans and Zuckerman, 2008). Our cross-sectional empirical strategy substantiates the association between these two factors but does not allow us to identify the direction of causality. Thus, our estimates of the effects of information exchange may be biased upwards and qualified as an upper-bound estimate. Nevertheless, our results provide support for a positive association between productivity and being well connected locally in networks of information exchange, and our counterintuitive finding regarding brokerage suggests that at the very least, it does not improve fisher productivity. Future work should build on our approach by identifying appropriate instrumental variables (see Wooldridge, 2010) or by leveraging dynamic network data to account for network formation processes and exploit lagged outcomes to firmly establish causal relationships.

In spite of these limitations, this research fills a critical gap in the literature regarding the costs and benefits of cooperation in the harvest of common-pool fishery resources. By explicitly investigating the relationship between strategic information exchange and fisher productivity, our results shed light on social-structural dynamics that help form the foundation for fisher decision-making and behavior. The social dynamics underpinning fisher behavior and decision-making have received very little attention in the literature compared to fish ecology and fish stock dynamics, yet understanding these dynamics is critical for devising effective fisheries management strategies that meet societal goals (Barnes et al., 2016a; Branch et al., 2006; Hicks et al., 2016) and avoid widespread fisheries collapse (Hilborn, 1985). Here, we demonstrated that while there is clearly an economic benefit associated with cooperation across temporal scales in the harvest of common-pool fishery resources, engaging in strategic information exchange across social divides is associated with a clear economic disadvantage. More fully understanding these relationships, why some fishers still choose to broker, and the stability of brokerage over time and in the face of external shocks should be the focus of future research.

References

Abbasi, A., Altmann, J., Hossain, L., 2011. Identifying the effects of co-authorship networks on the performance of scholars: A correlation and regression analysis of performance measures and social network analysis measures. Journal of Informetrics 5, 594-607.

Abbasi, A., Wigand, R.T., Hossain, L., 2014. Measuring social capital through network analysis and its influence on individual performance. Library & Information Science Research 36, 66-73.

Acheson, J.M., 1975. The lobster fiefs: economic and ecological effects of territoriality in the Maine lobster industry. Human Ecology 3, 183-207.

Alesina, A., Gennaioli, C., Lovo, S., 2014. Public goods and ethnic diversity: Evidence from deforestation in Indonesia. NBER Working Paper No. 20504, National Bureau of Economic Research.

Alesina, A., La Ferrara, E., 2002. Who trusts others? Journal of Public Economics 85, 207-234.

Aral, S., Van Alstyne, M., 2011. The diversity-bandwidth trade-off1. American Journal of Sociology 117, 90-171.

Bailey, F.G., 1963. Politics and society in contemporary Orissa, in: Phillips, C.H. (Ed.), Studies on Modern Asia and Africa: Politics and Society in India. Allen & Unwin, London, UK.

Banerjee, A., Chandrasekhar, A.G., Duflo, E., Jackson, M.O., 2013. The diffusion of microfinance. Science 341.

Barnes, M., Lynham, J., Kalberg, K., Leung, P.S., 2016a. Social networks and environmental outcomes. Proceedings of the National Academy of Sciences In press.

Barnes, M.L., Kalberg, K., Pan, M., Leung, P., 2016b. When is brokerage negatively associated with economic benefits? Ethnic diversity, competition, and common-pool resources. Social Networks 45, 55-65.

Barnes-Mauthe, M., Arita, S., Allen, S.D., Gray, S.A., Leung, P.S., 2013. The influence of ethnic diversity on social network structure in a common-pool resource system: Implications for collaborative management. Ecology and Society 18, 23.

Barnes-Mauthe, M., Gray, S.A., Arita, S., Lynham, J., Leung, P., 2014. What determines social capital in a social–ecological system? Insights from a network perspective. Environmental Management 55, 392-410.

Béné, C., 1996. Effects of market constraints, the remuneration system, and resource dynamics on the spatial distribution of fishing effort. Canadian Journal of Fisheries and Aquatic Sciences 53, 563-571.

Bizzi, L., 2013. The Dark Side of Structural Holes A Multilevel Investigation. Journal of Management 39, 1554-1578.

Bodin, Ö., Crona, B.I., 2009. The role of social networks in natural resource governance: What relational patterns make a difference? Global Environmental Change 19, 366-374.

Borgatti, S.P., 2002. NetDraw: Graph Visualization Software. Harvard: Analytic Technologies, Lexington, Kentucy, USA.

Borgatti, S.P., Jones, C., Everett, M.G., 1998. Network measures of social capital. Connections 21, 27-36.

Borgatti, S.P., Mehra, A., Brass, D.J., Labianca, G., 2009. Network analysis in the social sciences. Science 323, 892-895.

Branch, T.A., Hilborn, R., Haynie, A.C., Fay, G., Flynn, L., Griffiths, J., Marshall, K.N., Randall, J.K., Scheuerell, J.M., Ward, E.J., 2006. Fleet dynamics and fishermen behavior: Lessons for fisheries managers. Canadian Journal of Fisheries and Aquatic Sciences 63, 1647-1668.

Burt, R.S., 1992. Structural Holes: The Social Structure of Competition. Harvard University Press, Cambridge, MA, USA.

Burt, R.S., 2000. The network structure of social capital. Research in Organizational Behavior 22, 345-423.

Burt, R.S., 2005. Brokerage and Closure: An Introduction to Social Capital. Oxford University Press, New York, NY, USA

Chakravarty, S., Fonseca, M.A., 2014. The effect of social fragmentation on public good provision: An experimental study. Journal of Behavioral and Experimental Economics 53, 1-9.

Conley, T.G., Udry, C.R., 2010. Learning about a new technology: Pineapple in Ghana. The American Economic Review 100, 35-69.

Dreyfus-Leon, M., Gaertner, D., 2006. Modeling performance and information exchange between fishing vessels with artificial neural networks. Ecological Modelling 195, 30-36.

Evans, K.S., Weninger, Q., 2014. Information sharing and cooperative search in fisheries. Environmental and Resource Economics 58, 353-372.

Fafchamps, M., Minten, B., 2002. Returns to social network capital among traders. Oxford Economic Papers 54, 173-206.

Freeman, L.C., 1979. Centrality in social networks conceptual clarification. Social Networks 1, 215-239.

Gatewood, J.B., 1984. Cooperation, competition, and synergy: information-sharing groups among Southeast Alaskan salmon seiners. American Ethnologist, 350-370.

Gezelius, S.S., 2007. The social aspects of fishing effort. Human Ecology 35, 587-599.

Gintis, H., 2000. Beyond< i> Homo economicus</i>: evidence from experimental economics. Ecological Economics 35, 311-322.

Goffman, E., 1959. The presentation of self in everyday life, in: Newman, D.M., O'brien, J. (Eds.), Sociology: Exploring the Architecture of Everday Life Readings. Pine Forge Press, Thousand Oaks, CA, USA, pp. 120-129.

Gordon, H.S., 1954. The economic theory of a common-property resource: The fishery. The Journal of Political Economy 62, 124-142.

Greve, A., Benassi, M., Sti, A.D., 2010. Exploring the contributions of human and social capital to productivity. International Review of Sociology–Revue Internationale de Sociologie 20, 35-58.

Gruber, J.S., 2010. Key principles of community-based natural resource management: a synthesis and interpretation of identified effective approaches for managing the commons. Environmental management 45, 52-66.

Hardin, G., 1968. The tragedy of the commons. Science 162, 1243-1248.

Haynie, A.C., Hicks, R.L., Schnier, K.E., 2009. Common property, information, and cooperation: Commercial fishing in the Bering Sea. Ecological Economics 69, 406-413.

Hicks, C.C., Levine, A., Agrawal, A., Basurto, X., Breslow, S.J., Carothers, C., Charnley, S., Coulthard, S., Dolsak, N., Donatuto, J., 2016. Engage key social concepts for sustainability. Science 352, 38-40.

Hilborn, R., 1985. Fleet dynamics and individual variation: why some people catch more fish than others. Canadian Journal of Fisheries and Aquatic Sciences 42, 2-13.

Jentoft, S., 2007. Limits of governability: Institutional implications for fisheries and coastal governance. Marine Policy 31, 360-370.

Kalberg, K., Pan, M., forthcoming. 2012 Economic Cost-Earnings of Pelagic Longline Fishing in Hawaii. Pacific Islands Fisheries Science Center, NOAA Technical Memorandum.

Krackhardt, D., 1999. The ties that torture: Simmelian tie analysis in organizations. Research in the Sociology of Organizations 16, 183-210.

Levin, S.A., Lubchenco, J., 2008. Resilience, robustness, and marine ecosystem-based management. BioScience 58, 27-32.

Lin, N., 1999. Building a network theory of social capital. Connections 22, 28-51.

McPherson, M., Smith-Lovin, L., Cook, J.M., 2001. Birds of a feather: Homophily in social networks. Annual Review of Sociology, 415-444.

Millischer, L., Gascuel, D., Drouineau, H., Mahévas, S., Pelletier, D., Beliaeff, B., Tejerina-Garro, F.L., de Mérona, B., Oberdorff, T., Hugueny, B., 2006. Information transfer, behavior of vessels and fishing efficiency: an individual-based simulation approach. Aquatic Living Resources 19, 1-13.

Molina ‐ Morales, F.X., Martínez ‐ Fernández, M.T., 2009. Too much love in the neighborhood can hurt: how an excess of intensity and trust in relationships may produce negative effects on firms. Strategic Management Journal 30, 1013-1023.

Mueller, K.B., Taylor, W.W., Frank, K.A., Robertson, J.M., Grinold, D.L., 2008. Social networks and fisheries: The relationship between a charter fishing network, social capital, and catch dynamics. North American Journal of Fisheries Management 28, 447-462.

Nkhata, A.B., Breen, C.M., Freimund, W.A., 2008. Resilient social relationships and collaboration in the management of social-ecological systems. Ecology and Society 13, 2.

NOAA, 2006. Magnuson-Stevens Fishery Conservation and Management Reauthorization Act of 2006, Public Law no. 109-479, 120 Stat 3575 (2006), Washington, D.C., USA.

Nordyke, E.C., 1989. The Peopling of Hawai‘i. University of Hawaii Press, Honolulu, HI.

Olson, M., 1965. Logic of Collective Action: Public Goods and the Theory of Groups. Harvard University Press, Cambridge, MA, USA.

Ostrom, E., 1990. Governing the Commons: The Evolution of Institutions for Collective Action. Cambridge University Press, Cambridge, UK.

Ostrom, E., 2000. Collective action and the evolution of social norms. The Journal of Economic Perspectives 14, 137-158.

Pan, M., Chan, H., Kalberg, K., 2014. Tracking the Changes of Economic Performance Indicators for the Main Commercial Fisheries in the Western Pacific Areas 2012 Update. Pacific Islands Fisheries Science Center Internal Report (IR-14-017), Honolulu, HI, p. 18.

Podolny, J.M., Baron, J.N., 1997. Resources and relationships: Social networks and mobility in the workplace. American sociological review, 673-693.

Pollnac, R.B., Carmo, F., 1980. Attitudes toward cooperation among small-scale fishermen and farmers in the Azores. Anthropological Quarterly, 12-19.

Pomeroy, R., Parks, J., Pollnac, R., Campson, T., Genio, E., Marlessy, C., Holle, E., Pido, M., Nissapa, A., Boromthanarat, S., 2007. Fish wars: Conflict and collaboration in fisheries management in Southeast Asia. Marine Policy 31, 645-656.

Poteete, A.R., Ostrom, E., 2004. Heterogeneity, group size and collective action: The role of institutions in forest management. Development and Change 35, 435-461.

Pradhan, N.C., Sharma, K.R., Leung, P., 2003. Analyzing technical and economic interrelationships in Hawaii's longline fishery. Marine Resource Economics 18, 167-194.

Rogers Everett, M., 1995. Diffusion of Innovations, 4th ed. The Free Press, New York, NY, USA.

Salas, S., Gaertner, D., 2004. The behavioural dynamics of fishers: Management implications. Fish and Fisheries 5, 153-167.

Scott, A., 1955. The fishery: The objectives of sole ownership. The Journal of Political Economy 63, 116-124.

Stovel, K., Golub, B., Milgrom, E.M.M., 2011. Stabilizing brokerage. Proceedings of the National Academy of Sciences 108, 21326-21332.

Stovel, K., Shaw, L., 2012. Brokerage. Annual Review of Sociology 38, 139-158.

Tajfel, H., Turner, J.C., 1979. An integrative theory of intergroup conflict, in: Austin, W.G., Worchel, S. (Eds.), The Social Psychology of Intergroup Relations. Brooks-Cale, Monterey, CA, USA, pp. 33-47.

Tsai, W., Ghoshal, S., 1998. Social capital and value creation: The role of intrafirm networks. Academy of Management Journal 41, 464-476.

Turner, R.A., Polunin, N.V.C., Stead, S.M., 2014. Social networks and fishers' behavior: Exploring the links between information flow and fishing success in the Northumberland lobster fishery. Ecology and Society 19.

Varughese, G., Ostrom, E., 2001. The contested role of heterogeneity in collective action: Some evidence from community forestry in Nepal. World Development 29, 747-766.

Wilson, J.A., 1990. Fishing for knowledge. Land Economics 66, 12-29.

Wooldridge, J.M., 2010. Econometric analysis of cross section and panel data. MIT press.

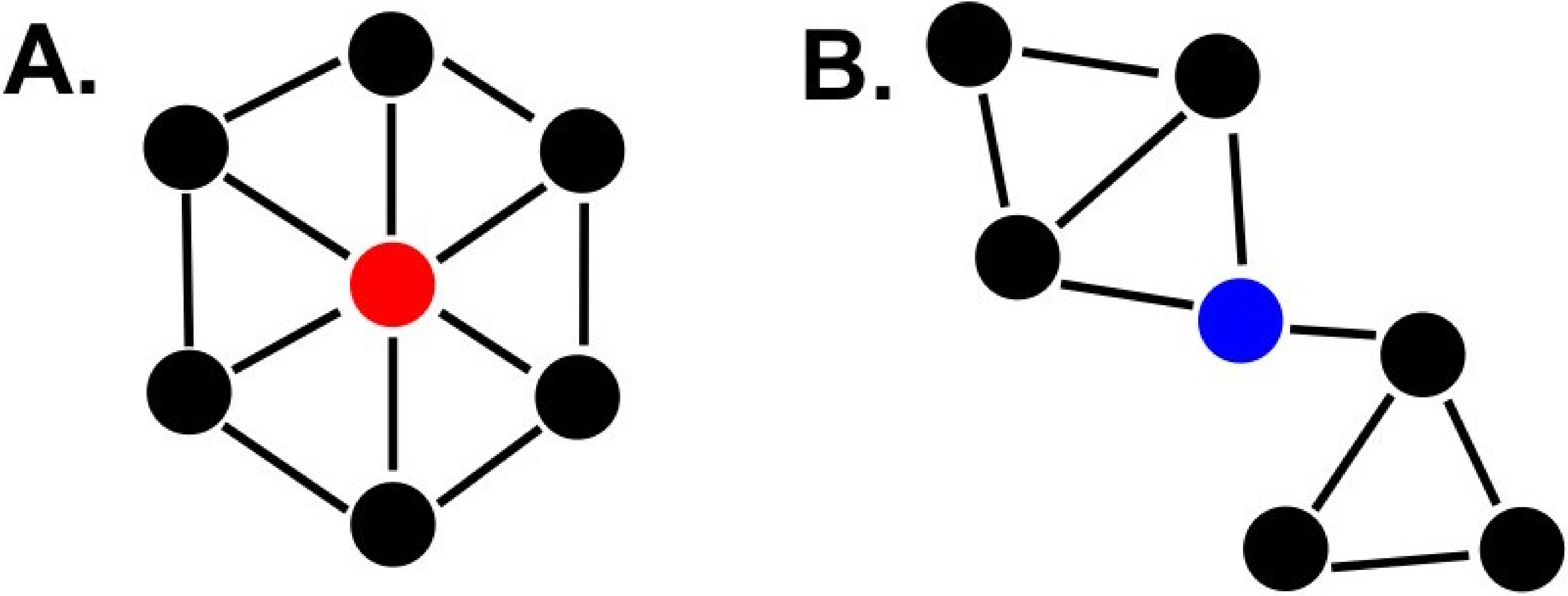
Xiao, Z., Tsui, A.S., 2007. When brokers may not work: The cultural contingency of social capital in Chinese high-tech firms. Administrative Science Quarterly 52, 1-31.

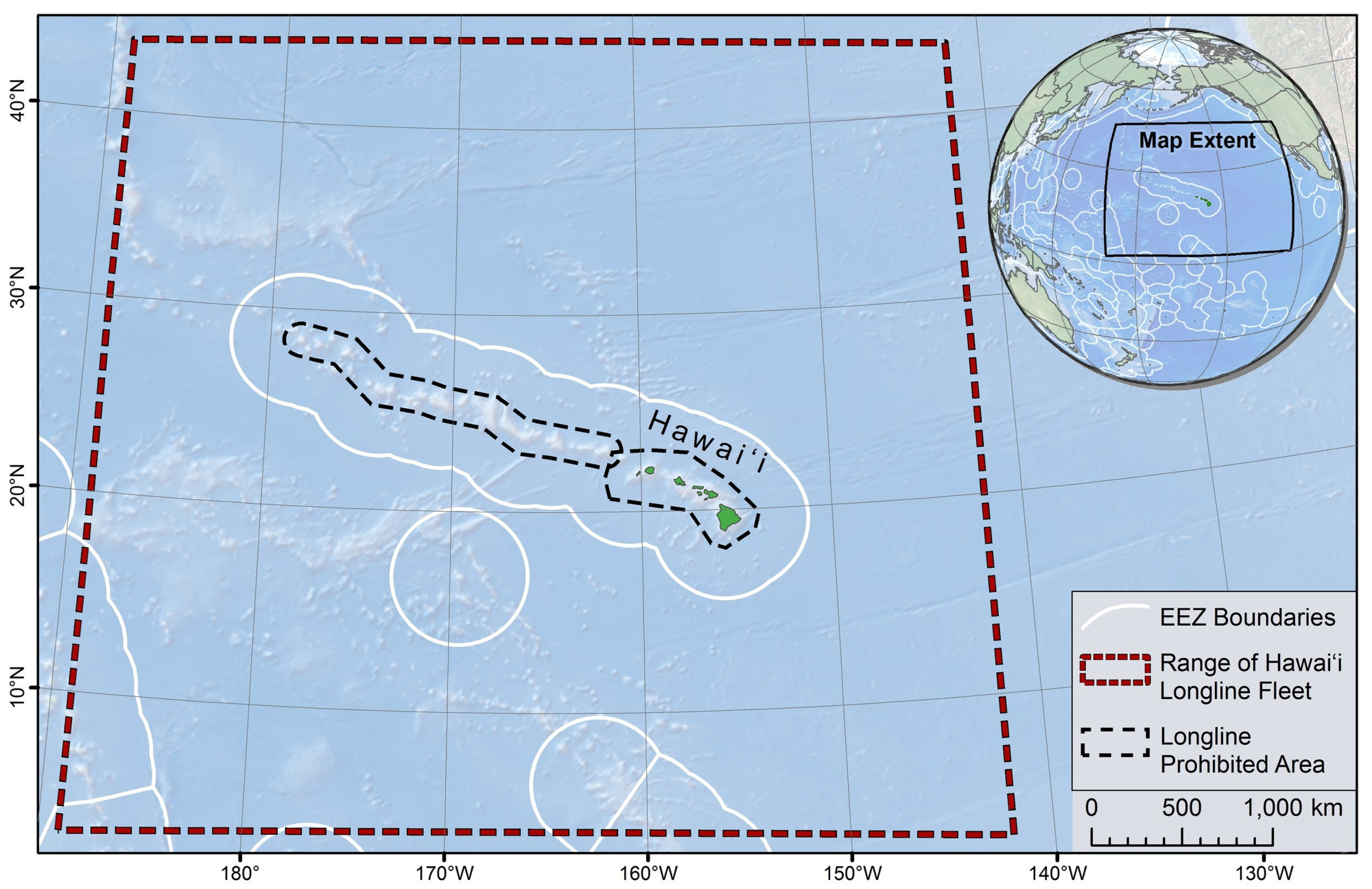
Figure Captions:

Figure 1. An example of network prominence (A) and brokerage (B). Network prominence can be captured by degree centrality, which corresponds to the number of direct ties one has in a network. In network A, the node with the greatest number of ties (where degree centrality = 6) is shaded in red. Brokers act as intermediaries in networks by linking isolated individuals or disparate groups. In network B, the blue shaded node is acting as a broker.

Figure 2. Map identifying the study area and the range of Hawaii's longline fleet, adapted from Barnes et al. (2016b).

Figure 3. Graphical depictions of (A) vessel owner's information exchange network used to access and share long-term information on vessel technology, hiring captain or crew, gear maintenance, and fishing regulations; and (B) vessel operator's information exchange network used to access and share short-term information on fish activity, site catch/set location, bycatch, and weather. By vessel owner, we mean all fishers who own a vessel. By vessel operator, we mean all fishers who operate their vessel, including both hired captains and owners who operate their vessel themselves (owner-operators). Each shape or node represents an actor in the network, and the lines or edges connecting them represent their information exchange ties. V-A, E-A, and K-A refer to each ethnic group (Vietnamese-American, Euro-American, and Korean-American, respectively). The network was created in NetDraw (Borgatti, 2002) using the spring embedding algorithm with node repulsion, which uses iterative fitting to place nodes closest to those they have the shortest path lengths to while minimizing overlap.


A.
B.



Map Extent
Hawai'i
EEZ Boundaries
Range of Hawai'i Longline Fleet
Longline Prohibited Area
0
500
1,000 km
40°N
30°N
20°N
10°N
180°
170°W
160°W
150°W
140°W
130°W

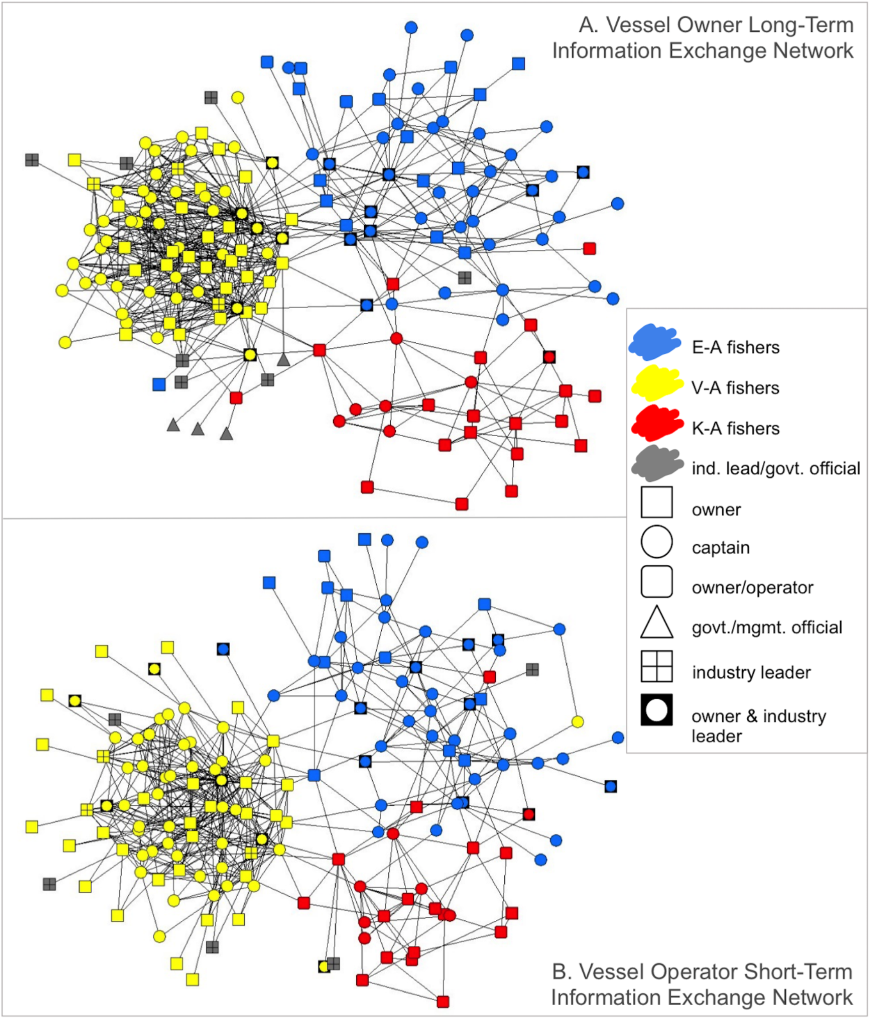

A. Vessel Owner Long-Term Information Exchange Network
E-A fishers
V-A fishers
K-A fishers
ind. lead/govt. official
owner
captain
owner/operator
govt./mgmt. official
industry leader
owner & industry leader
B. Vessel Operator Short-Term Information Exchange Network

Table 1. Description of input, vessel, and owner and operator specific variables.

Variable	Description
Capital and labor	
Trip days	Total trip length (in days), including days spent on travel
Crew size	Number of persons on the boat, including the operator
Fixed cost	Annual fixed operating costs ($/yr), including dry dock, engine work, technology upgrades, and continuous maintenance
Variable cost	Annual variable operating costs ($/yr), i.e., total annual trip-level costs, including fuel, bait, ice, and other miscellaneous items (used in vessel owner analysis)
Other input	Trip-level variable operating costs ($/trip), including fuel, bait, ice, and other miscellaneous items (used in vessel operator analysis)
Human capital	
Education	Value 1 if the owner or operator had some college education, 0 otherwise
Experience	Owner or operator's fishing experience (years)
Information exchange variables	
Network prominence	
Centrality (indegree)	Number of incoming ties identified as important for exchanging long-run information (owners); number of incoming ties identified as important for exchanging short-run information (operators)
Brokerage	
Efficiency	A measure of an optimized network that idealizes non-redundant contacts. Calculated for owners using the long-run information exchange network, and operators using the short-run information exchange network (see section 3.4)
Inter-ethnic ties	Total number of inter-ethnic ties in the long-run information exchange network (owners); total number of inter-ethnic ties in the short-run information exchange network (operators)
Vessel specific variables	
Target: swordfish	Value 1 if the vessel targeted swordfish for at least 1 trip in 2012, 0 otherwise (targeted tuna only)
Vessel age	Age of vessel as of 2013
Vessel size: small	Value 1 if the vessel is a small size (≤ 55 feet), 0 otherwise
Vessel size: medium	Value 1 if the vessel is a medium size (>55 feet and <74 feet), 0 otherwise
Owner specific variables	
Owner-operated	Value 1 if the vessel was owner-operated, 0 otherwise (hired captain)
Ethnicity: Euro-American	Value 1 if the owner/operator is Euro-American, 0 otherwise
Ethnicity: Korean-American	Value 1 if the owner/operator is Korean-American, 0 otherwise

Table 2. Summary statistics for variables in vessel owner's annual-level production function, 2012 (n = 91 fishing vessels).

Variable	Unit	Mean	Std. dev
Output (annual revenue)	USD	$758,062.30	$275,751.80
Capital and labor			
Trip days	days/yr	254.703	210.991
Crew size	no. of persons	5.810	0.710
Fixed cost	$/yr	$98,734.49	$36,845.37
Variable cost	$/yr	$343,420.10	$102,752.60
Human capital			
Education	some college or above = 1	0.495	0.503
Experience	years fishing	27.962	12.215
Information exchange variables (long-term)			
Network prominence			
Centrality (indegree)	no. of incoming ties	12.044	14.705
Brokerage			
Efficiency	no. of non-redundant contacts/ total no. of contacts	0.836	0.091
Inter-ethnic ties	no. of inter-ethnic ties	1.802	2.177
Vessel specific variables			
Target: swordfish	yes = 1	0.154	0.363
Vessel age	years	27.846	10.421
Vessel size: small	yes = 1	0.099	0.3
Vessel size: medium	yes = 1	0.44	0.499
Owner specific variables			
Owner-operated	yes = 1	0.352	0.48
Ethnicity: Euro-American	yes = 1	0.374	0.486
Ethnicity: Korean-American	yes = 1	0.165	0.373

Table 3. Summary statistics for variables included in vessel operator's trip-level production function, 2012 (n = 853 tuna fishing trips).

Variable	Unit	Mean	Std. dev
Output (trip revenue)	USD	$67,739.81	$33,606.92
Capital and labor			
Trip days	days/trip	22.535	5.408
Crew size	no. of persons	4.682	0.672
Other input	$/trip	$29,683.97	$8,797.28
Human capital			
Education	some college or above = 1	0.258	0.438
Experience	years fishing	24.759	9.218
Information exchange variables (short-term)			
Network prominence			
Centrality (indegree)	no. of incoming ties	4.026	4.455
Brokerage			
Efficiency	no. of non-redundant contacts/ total no. of contacts	0.789	0.131
Inter-ethnic ties	no. of inter-ethnic ties	0.584	0.93
Vessel specific variables			
Vessel age	years	26.498	10.113
Vessel size: small	yes = 1	0.134	0.341
Vessel size: medium	yes = 1	0.406	0.491
Owner specific variables			
Owner-operated	yes = 1	0.328	0.470
Ethnicity: Euro-American	yes = 1	0.409	0.492
Ethnicity: Korean-American	yes = 1	0.196	0.397

Table 4. Correlation coefficients among information exchange metrics

		Vessel Owners (long-term network)			Vessel Operators (short-term network)		
		1	2	3	1	2	3
1	Centrality (indegree)	1			1		
2	Efficiency	0.214	1		-0.123	1	
3	Inter-ethnic ties	0.628	0.563	1	0.203	0.277	1

Table 5. The role of information exchange on fisher productivity.

		Owner long-run model (annual; *n* = 91 vessels)		Operator short-run model (trip-level; *n* = 853 trips)	
	unit	Coef	SE	Coef	SE
Capital and labor					
Trip days	log	0.821***	0.249	0.767***	0.279
Crew size	log	0.260	0.266	0.083	0.180
Fixed cost (annual only)	log	0.101	0.088		
Variable cost (annual only)	log	0.299	0.204		
Other input (trip-level only)	log			0.610***	0.197
Human capital					
Education	yes = 1	-0.092	0.069	-0.109*	0.058
Experience	log	0.003	0.003	0.004	0.003
Information exchange variables					
Network prominence					
Centrality (indegree)	log	0.085**	0.037	0.050*	0.026
Brokerage					
Efficiency	log	-0.443*	0.235	-0.265***	0.100
Inter-ethnic ties	log	++	++	-0.202***	0.079
Vessel specific variables					
Target: swordfish (annual only)	yes = 1	-0.143*	0.075		
Vessel age	level	-0.006**	0.003	-0.007***	0.003
Vessel size: small	yes = 1	-0.154	0.127	0.016	0.114
Vessel size: medium	yes = 1	-0.026	0.070	0.167***	0.054
Owner specific variables					
Owner-operated	yes = 1	-0.059	0.062	0.030	0.050
Ethnicity: Euro-American	yes = 1	0.163*	0.096	0.283***	0.057
Ethnicity: Korean-American	yes = 1	-0.086	0.113	-0.063	0.077
Constant	level	3.450**	1.511	-2.054	1.405
R^2		0.802		0.338	
Adj. R^2		0.762		0.327	

*, **, *** denotes significance at the 0.10, 0.05, and 0.01 level. Standard errors were bootstrapped using 1,000 random samples.

++ Omitted due to collinearity (see Table 4).