SOCIAL NETWORKS MATTER:
LINKING RESOURCE USER’S SOCIAL BEHAVIOR TO COUPLED OUTCOMES
IN A MARINE SOCIAL-ECOLOGICAL SYSTEM

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Keywords: social networks, social capital, ethnic diversity, social-ecological system, fisheries, marine resource management
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DEDICATION

To my family, whose love, support, and encouragement has enabled me to reach beyond the realms of the imaginable.
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ABSTRACT

Effectively managing the current and unprecedented level of anthropogenic impacts on the natural environment requires a clear understanding of the interrelationships between people (the social system) and nature (the ecological system). Yet we currently lack essential information on the pro-social behavior of resource users, and the ways in which their social relationships may influence system-level outcomes. In this dissertation, I draw on sociological and economic theories related to social organization and social capital to investigate resource user’s social networks. I then examine their role in shaping environmental and economic outcomes in Hawaii’s ethnically diverse, longline fishery as an example social-ecological system (SES).

I begin by adopting a network perspective to investigate the role of ethnic diversity and other stakeholder attributes on individual levels of social capital, measured by network prominence, opportunities for brokerage, and tie strength. Social capital is an important resource that can be mobilized for purposive action or competitive gain. The distribution of social capital in SESs can determine who is more productive at extracting ecological resources, and who emerges as influential in guiding their management, thereby empowering some, while disempowering others. I find that ethnicity plays a significant role in the distribution of social capital, while human capital and social capital are also positively related. Surprisingly, my results suggest formal leadership plays an insignificant role on social capital, suggesting fishery representatives and industry leaders are presently not effective channels for information flow and likely lack the ability to influence the opinions of others. In interpreting these results I argue that one minority ethnic group has succeeded in establishing a productive ethnic enclave driven by a turbulent period of settlement and resettlement as refugees. In contrast, I argue that a lack of basic social capital resources among another minority ethnic group with a less formidable history has decreased their ability to adapt to policy and environmental changes, leading to a breakdown in their participation in the fishery.

Next, I link data on fisher’s social networks to detailed data on catch and effort over a period of five years to empirically estimate the relationship between information sharing relationships and rates of incidental catch (i.e., ‘bycatch’) – a pressing global environmental issue. The network exhibits strong homophily, with fishers organizing themselves into three information sharing network groups largely corresponding to ethnicity. Controlling for spatiotemporal factors, I find significant differences in shark bycatch among the three network groups. Moreover, bycatch
rates for individuals whose majority of ties fall outside their ethnic group are more closely aligned with their network group, rather than their ethnic group. Significant differences in shark bycatch among network groups hold when controlling for spatiotemporal factors and vessel and operator specific variables known to effect shark bycatch. These results provide novel empirical evidence that network homophily is related to environmental outcomes, and indicate that social affiliations are tied to behaviors that can have a direct impact on ecosystems. I argue that the effect captured here relates to diffusion and strategic information sharing (or lack thereof) mediated by ethnic boundaries and social exclusion.

In my final essay, I link fisher’s social network data to vessel cost-earnings data to econometrically evaluate the role of individual social capital on vessel economic performance. Social capital has proven to be a significant factor influencing economic outcomes in a variety of settings, yet there is little evidence of this effect in SESs. Many SESs are characterized by high levels of uncertainty and competition over limited resources, where the benefits of occupying advantageous structural positions in information sharing networks is likely enhanced. Controlling for common factors of production, I find that social capital in the form of local network prominence is positively related to economic productivity, while inter-ethnic ties as a measures of brokerage has a negative effect. I argue that social differentiation across ethnic groups inflated by high levels of competition causes actors that bridge ethnic divides to be penalized for associating with other groups, consistent with theories of social identity.

Taken together, this research contributes novel empirical evidence that contributes to the literature on social networks and social capital in SESs and among ethnically diverse populations. The primary takeaway is that social networks matter, and ethnic diversity plays a substantial role in mediating their effects on a diverse range of outcomes. These outcomes are relevant for achieving resource governance that is not only ecologically and economically sustainable, but also equitable.
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<td>SES(s)</td>
<td>Social-Ecological System(s)</td>
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<td>CPR</td>
<td>Common-Pool Resource</td>
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<tr>
<td>HLF</td>
<td>Hawaii’s Longline Fishery</td>
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<tr>
<td>V-A</td>
<td>Vietnamese-American</td>
</tr>
<tr>
<td>K-A</td>
<td>Korean-American</td>
</tr>
<tr>
<td>E-A</td>
<td>European-American</td>
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<tr>
<td>TAC</td>
<td>Total Allowable Catch</td>
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<tr>
<td>NOAA</td>
<td>National Oceanic and Atmospheric Administration</td>
</tr>
<tr>
<td>WCPO</td>
<td>Western and Central Pacific Ocean</td>
</tr>
<tr>
<td>EPO</td>
<td>Eastern Pacific Ocean</td>
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<tr>
<td>SNA</td>
<td>Social Network Analysis</td>
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<td>GLM</td>
<td>General Linear Model</td>
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<td>ANCOVA</td>
<td>Analysis of Covariance</td>
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<tr>
<td>CPUE</td>
<td>Catch Per Unit Effort</td>
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<tr>
<td>RMFO</td>
<td>Regional Fishery Management Organization</td>
</tr>
<tr>
<td>NMFS</td>
<td>National Marine Fisheries Service</td>
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<tr>
<td>HDAR</td>
<td>Hawaii Department of Agriculture</td>
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<tr>
<td>PIFSC</td>
<td>Pacific Islands Fisheries Science Center</td>
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<tr>
<td>PIRO</td>
<td>Pacific Islands Regional Office</td>
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Chapter 1

INTRODUCTION

Marine and other environmental systems are currently facing substantial pressure from a host of anthropogenic drivers that threaten their long-term sustainability (Pauly et al. 1998, Jackson et al. 2001, Sumaila 2012). Linking social and ecological components of environmental systems is therefore critical for the analysis of almost any action related to securing long-term sustainability (Folke et al. 2007, Goudie 2013). Recognizing this, research on the environment is increasingly focused on transcending traditional disciplinary boundaries and embracing an integrative, complex systems view that explicitly considers the interrelationships between people (the social system) and nature (the ecological system). From this perspective, environmental systems can be understood as linked social-ecological systems (SESs) (Berkes et al. 2003), comprised of an ecological unit, and social unit, and the interactions and feedbacks between them (Fig. 1.1).

Figure 1.1 Conceptual Diagram of a Social-Ecological System. Social-ecological systems (SESs) are comprised of an ecological unit, e.g., fisheries and the ecosystem on which they depend, a social unit, e.g., fishers and coastal communities, and the interactions and feedbacks between them. Ecological systems provide ecosystem goods and services that support human well-being (I), while social systems feed back on ecological systems through human impacts and modifying forces (II). Adapted from Kittinger et al. (2012).
Complexity is a classic characteristic of SESs, emerging from the dynamic interaction of ecological, economic, and social factors that influence system outcomes. In marine systems, this complexity is often compounded by the common-pool nature of ocean resources (Hardin 1968, Ostrom et al. 1999, Dietz et al. 2003). Progress has been made to unpack these systems (Gardner et al. 1990, Ostrom 1990, Agrawal 2003, Barnes-Mauthe et al. 2013) and capture their complexity into formal models (Castillo and Saysel 2005, Ostrom 2009), yet we still lack a thorough understanding of their socio-economic aspects which are driven by human behavior, which is crucial for supporting effective management and policy development (Ostrom et al. 1999, Salas and Gaertner 2004, Branch et al. 2006, Hilborn 2007). Indeed, Hilborn (1985) argues that the collapse of several fisheries, which exhibit classic common-pool characteristics, can be attributed to an inadequate understanding of fisher behavior rather than the biological and ecological attributes of fisheries systems, and the failure to incorporate such knowledge into fisheries management schemes.

1.1 Common-Pool Resources and Human Behavior

Common-pool resources (CPRs) have two defining characteristics: nonexcludability and rivalry (also referred to as ‘subtractability’). Nonexcludability refers to the fact that excluding individuals from extracting or otherwise benefiting from the resource through any physical and/or institutional means is either impossible or impractical (i.e., the system exhibits an ‘open access’ characteristic), while rivalry defines resources in which exploitation by one user reduces resource availability for others (Ostrom et al. 1994). Under classic economic theory, which assumes a rational individual acting in their own self-interest, CPR systems are trapped in what has been termed the CPR dilemma, where they are plagued with inefficiencies, overexploitation and underinvestment in long-term sustainability (Gordon 1954, Scott 1955, Hardin 1968). Marine fisheries present a classic example of the CPR dilemma, also famously referred to as “the tragedy of the commons” by Garret Hardin (1968). Fisheries resources form a natural capital stock which can be depleted by harvesting, and therefore harvesting is rivalrous because a fish landed by one fisher is no longer available for another (Grafton 2005). Due to the mobility and range of most fisheries resources, coupled with the high cost of monitoring individual fishers, it is typically impractical, if not impossible, to exclude outsiders from harvesting (Grafton 2005). Under these conditions the theory states that fishers, acting as rational individuals pursuing their own self-interest, will overinvest in resource extraction and attempt to extract the resource at a rapid rate (i.e., before others do), causing overexploitation and resource depletion.
(Gordon 1954, Scott 1955, Hardin 1968). In addition, resource users will free-ride off of the efforts of others, and will choose to defect from attempts at cooperative arrangements (Schlager 2002). As Schlager (2002) states, “in such situations, individual rationality results in collective irrationality,” where individuals following their own short-term interests produce outcomes that are not in anyone’s long-term interest (Ostrom et al. 1999).

The theory of the rational, self-interested and non-cooperative actor in CPR settings has strong theoretical and empirical support, and has been the foundation of many formal models (e.g., Gordon 1954, Scott 1955, Hardin 1968). However, recent research has emphasized that the interactions between humans and CPRs are often much more complex than these models suggest, with human decision-making behavior often deviating from their predictions (Ostrom 1990, Ostrom and Walker 1991, Ostrom et al. 1994, Schlager 2002). Specifically, actors in CPR settings have been found to be cooperative and pro-social ways not predicted by formal economic models (Ostrom 1990, Gintis 2000). In reference to this phenomena, Gintis (2000) states that despite the predictions of our formal economic models, in many circumstances actors have proven to be strong reciprocators “who come to strategic interactions with a propensity to cooperate” and “respond to cooperative behavior by maintaining or increasing cooperation” (p. 311). One factor which has been shown to be crucially important in these settings for influencing this perplexing pro-social and cooperative behavior is the ability to communicate and share information. Indeed there is now a large body of experimental evidence showing that communication among resource users significantly influences cooperation, leading to increased group payoffs (Orbell et al. 1988, Ostrom and Walker 1991, Ostrom et al. 1994, Kollock 1998, Kopelman et al. 2002).

Despite this recent progress toward a more comprehensive theory of human behavior in CPR systems, we still lack a thorough understanding of the factors that influence cooperation and pro-social behaviors, and the role of communication on outcomes, particularly in diverse settings plagued with uncertainty. Yet it is clear that in developing solutions to CPR dilemmas, management institutions need to address human behavior (Hilborn 2007, Jager and Mosler 2007). Though people may adopt individualistic decision strategies as proposed by the classic economic rational actor model, in some cases people may elect to employ social decision strategies (Jager and Mosler 2007). For example, people may observe other’s behavior, or may directly ask others for information and advice (Cialdini and Goldstein 2004, Jager and Mosler 2007). Considering these social processes have direct effects on the diffusion of new behaviors
and practices (Rogers 1979), social networks, or relationships among individuals, likely play a pivotal role here (Jager and Mosler 2007).

1.2 Social Networks, Social Capital, and Marine Fisheries

Social networks are informal social systems which are held together by pro-social behaviors, and can consist of different types of social relationships, from casual to close ties (Wasserman and Faust 1994). Originating in the field of sociology, social network theory states that the people with whom we interact serve as channels for the flow of information, informal insurance and risk sharing, and thus have the ability to impact our decision making, beliefs and behaviors (Wasserman and Faust 1994, Lin 1999, Jackson 2008). The social network approach therefore uncovers the role of interactions and patterned relationships among actors in order to better understand behavioral and decision-making processes. Theoretical and empirical evidence has shown that social networks can influence cognition and social perception (Freeman et al. 1987, Krackhardt 1987), exchange and power (Cook and Emerson 1978, Cook et al. 1983, Markovsky et al. 1988, Ibarra 1993), consensus and social influence (Doreian 1981, Friedkin 1986, Friedkin and Cook 1990, Marsden and Friedkin 1993), social learning (Liebeskind et al. 1996, Conley and Udry 2001, Borgatti and Cross 2003), group problem solving (Bavelas 1950, Bavelas and Barrett 1951, Leavitt 1951), and the diffusion and adoption of innovations (Coleman et al. 1957, Rogers 1979, Valente 1996). These diverse benefits embedded in and facilitated by social networks have been highlighted by many recent studies (Borgatti et al. 1998, Lin 1999, Burt 2000, Grafton 2005, Granovetter 2005, Jackson 2008, Bodin and Prell 2011).

Pelagic marine fisheries, where individuals operate in a heterogeneous, chaotic environment and face high levels of uncertainty on a daily basis, are perhaps the most dynamic and complex of all CPR systems (Barnes-Mauthe et al. 2012). Pelagic marine fisheries are commonly characterized by highly migratory resources traversing jurisdictional boundaries, and extraction occurs in a chaotic open ocean environment where rapid, unpredictable fluctuations are known to occur due to various biological and ecological factors (Wilson 2002). Fishers not only learn from their past experiences in order to cope with this complexity, but also rely on sharing information with others within their social networks in order to enhance their decision making (Wilson 1990, Branch et al. 2006, Barnes-Mauthe et al. 2013). In this context, fisher’s social networks may consist of other fishers in addition to industry leaders, fishery scientists, fishery management officials, fishing supply store owners, or any other individual they may share
information with in order to dampen the uncertainty generally associated with fishing (Barnes-Mauthe et al. 2012, Barnes-Mauthe et al. 2013). In building these information sharing relationships with various stakeholders, fishers can accrue social capital (Figure 1.2).

![Diagram of Social Capital](image)

**Figure 1.2 The Three Dimensions of Social Capital.** See Nahapiet and Ghosal (1998) and Tsai and Ghosal (1998).

The theory of social capital, broadly stated, captures the idea that social bonds facilitate trust and reciprocity and the establishment of shared norms and values which can be valuable for people and communities (Bourdieu 1986, Coleman 1988). For example, social relationships, and the information and resources embedded within them, can provide advantages to those that are better, or strategically connected (Granovetter 1985, Lin 1999, Fafchamps and Minten 2002), and social cohesion can facilitate cooperation and collective action (Adger 2003, Ostrom and Ahn 2009). The concept originated within the field of sociology with a focus on the benefits accruing to individuals and small groups via their social relationships (Bourdieu 1986, Coleman 1988). Yet the concept was quickly expanded by various scholars to include many aspects of social life, such as trust, reciprocity, exchanges, and shared norms and values (Nahapiet and Ghoshal 1997, Tsai and Ghoshal 1998, Lin 1999, Woolcock 2001, Pretty 2003). Due to this broad and sometimes vague interpretation of social capital, the concept has generally been plagued with controversy about its precise meaning and effects (Portes 1998b). To a degree
there has been a consensus among scholars that social capital refers to the ability of human actors to secure benefits via membership in social structures or networks (Granovetter 1985, Portes and Sensenbrenner 1993, Portes 1998a, Lin 1999, Burt 2000, Putnam 2001), however some still argue that the concept includes not only this structural social network dimension, but also a cognitive and relational dimension comprised of shared norms/values and trust, respectively (Figure 1.2) (Nahapiet and Ghoshal 1997, 1998, Tsai and Ghoshal 1998, Woolcock and Narayan 2000, Pretty and Ward 2001). There also remains some disagreement about whether social capital resides among individuals or groups, and the most appropriate ways to measure it. This debate is discussed in detail in Chapter 3. Adopting the multidimensional perspective of social capital (Fig. 1.2), my primary focus in this thesis is on the structural dimension of social capital, here referred to simply as ‘social capital.’ However, it is important to keep in mind that at its core, social capital resides in the social fabric that ties people and communities together, and its different dimensions are inherently highly interrelated.

1.3 Objectives

Social capital is known to influence economic outcomes (see Jackson 2010), and recent research also suggests that social networks and the social capital they constitute may play a key role in influencing environmental outcomes (e.g. Sekhar 2007, Bodin and Crona 2008, Bodin and Prell 2011). Yet previous research has not explicitly examined the relationship between social networks and social capital among resource users and economic and environmental outcomes in the context of a social-ecological system. Moreover, we currently have a very poor understanding of the antecedents of social capital in general (but see Lin and Huang 2005, Ramirez-Sanchez 2011), making it difficult to predict how information and behaviors might diffuse through networks of stakeholders without having explicit social network information, which is often difficult to obtain. In addition, much of the previous research on social capital has neglected to consider the potential effect of ethnic diversity among actors. Ethnic diversity among actors has recently been shown to influence social network structure in a SES (Barnes-Mauthe et al. 2013), and is therefore likely to influence variation in social capital among resource users. This thesis seeks to fill this knowledge gap by examining information sharing networks and social capital in Hawaii’s ethnically diverse, pelagic longline fishery as an example of a marine SES. Specifically, in this thesis I adopt a network perspective to examine how ethnic diversity and other human capital attributes influence social capital among individual fishers.
(Chapter 3), and how social relationships influence environmental and economic outcomes (Chapter 4 and 5, respectively).

1.4 Dissertation Organization

This research comprises a series of three separate, but related inquiries (Chapters 3-5). Each inquiry will draw on a comprehensive information sharing social network data set on resource users in Hawaii’s longline fishery (HLF), which can be characterized as an ethnically diverse marine SES. The study system and network data are described in detail in Chapter 2. In Chapter 3, I adopt a network perspective and draw on previous research and theory to establish and calculate relevant measures of social capital. I then empirically test how ethnic diversity and human capital attributes contribute to variation within them to provide a better understanding of what determines social capital in a SES. I then turn to examining social networks and social capital influence outcomes in the HLF. Specifically, in Chapter 4 I provide the first explicit linkage between resource user’s social networks and environmental outcomes by showing that social network characteristics are significantly related to rates of incidental catch (i.e., bycatch). Finally, in Chapter 5 I examine how resource user’s information sharing networks influence economic outcomes by empirically testing the role of social capital on fisher productivity.

1.5 Primary Contribution

This research provides critical information on socioeconomic and human behavioral aspects of SESs that affect both environmental and economic outcomes, yet at present remain poorly understood. This research is the first in the natural resource management literature to establish individual network measures of social capital, their antecedents, and their role in providing resource users with economic benefits. Perhaps most importantly, this research provides novel empirical evidence that social affiliations are tied to behaviors that can scale up to have a direct impact on ecosystems. This research is therefore relevant to broad range of SESs, having important implications for management and policy.
References


Jackson, M. O. 2010. An Overview of Social Networks and Economic Applications.in J. Benhabib, A. Bisin, and M. O. Jackson, editors. The Handbook of Social Economics. Elsevier Press, Stanford, CA, USA.


Chapter 2

STUDY SYSTEM

2.1 Hawaii’s Longline Fishery

Hawaii’s longline fishery (HLF) is a limited-entry, multimillion-dollar pelagic fishery supplying domestic and international markets with fresh tuna and swordfish, and is the largest commercial fishing sector in the Hawaiian Islands. In 2012, there were 129 active vessels that completed 19,424 fishing sets on 1,437 trips, which generated approximately USD $94 million in fishing revenue (WPACFIN 2012). Although Hawaii is comprised of a diverse, multicultural background (see Nordyke 1989, Haas 1998), the fishery is comprised of only three rather distinct ethnic groups: Vietnamese-American (V-A) fishers (~ 56 vessels); European-American (E-A) fishers (~ 41 vessels); and Korean-American (K-A) fishers (~ 24 vessels) (Barnes-Mauthe et al. 2012, Barnes-Mauthe et al. 2013). The majority of K-A and V-A fishers are first generation immigrants who speak limited English, while E-A fishers are primarily individuals from the mainland United States (Barnes-Mauthe et al. 2012, Barnes-Mauthe et al. 2013, Allen et al. Unpublished Report). Nearly all vessels are home ported in Honolulu on the island of Oahu, though a handful of vessels intermittently fish in other fisheries, e.g., the longline fishery in American Samoa and various U.S. West Coast fisheries.

HLF operates year-round, with fishing trips lasting an average of three to four weeks. Fishing typically occurs in the Pacific Ocean both within, and outside of the United States’ Exclusive Economic Zone around the Hawaiian Islands (Figure 2.2). Tuna, primarily bigeye (*Thunnus obesus*) is targeted by all fishers with continuous deep-set mainlines that hang 2,000 - 3,000 baited hooks at depths of approximately 400 meters over a range of 25 - 45 nautical miles in the open ocean. A handful of V-A fishers also target swordfish (*Xiphias gladius*) for a portion of the year, where they employ shallow-set mainlines hanging approximately 700 - 1,000 baited hooks at depths of approximately 30 - 90 meters.

HLF is managed under the jurisdiction of the United States Magnuson-Stevens Act (NOAA 2006) and can be characterized as primarily consisting of institutional top-down management (see: [http://www.wpcouncil.org/pelagic/Pelagics%20FMP.html](http://www.wpcouncil.org/pelagic/Pelagics%20FMP.html)) (Barnes-Mauthe et al. 2012, Barnes-Mauthe et al. 2013). In addition to strict domestic regulations, such as area closures, gear restrictions, vessel monitoring systems, and mandatory onboard observers (100%
coverage for shallow-set swordfish trips, 20% coverage for deep-set tuna trips), the fishery is managed under a total allowable catch (TAC) on bigeye tuna assigned by international fishery management organizations. Bigeye tuna is currently classified as experiencing overfishing in the Western and Central Pacific Ocean (WCPO) and Eastern Pacific Ocean (EPO), meaning the rate of removal exceeds levels that can reasonably be sustained in the long-term. If the TAC is reached, the fishery is closed. In addition, all shallow-set swordfish trips are subject to an annual sea turtle interaction cap intended to protect vulnerable and endangered sea turtle populations, as sea turtles are more often incidentally caught at shallower depths.

With these restrictions having been enacted over the past decade, the fishery is considered well-regulated (Barnes-Mauthe et al. 2013). However, existing research suggests Hawaii’s longline fishers are currently facing mounting social and economic impacts due to the increase in regulation and augmented levels of competition (Pan et al. 2001, Allen and Gough 2006, Allen and Gough 2007, Barnes-Mauthe et al. 2012, Allen et al. Unpublished Report). For example, fishery closures stemming from concerns over exceeding the TAC on bigeye tuna typically occur toward the end of the calendar year, which overlaps with the busy holiday season when fresh tuna is in high demand throughout the Hawaiian Islands. Existing research also suggests management of HLF lacks sufficient representation of stakeholders, particularly given their geographic and cultural isolation (Allen and Gough 2007, Barnes-Mauthe et al. 2012, Barnes-Mauthe et al. 2013). International fishery management regulations the HLF is subject to are reviewed and updated every three years by the Western and Central Pacific Fisheries Commission and Inter-American Tropical Tuna Commission, the regional fishery management organizations that are responsible for the conservation and management of tuna and other marine resources in the WCPO and EPO, respectively. Though elected fishery representatives are invited to participate in official meetings, the vast majority of individual fishers operating in

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1 Bigeye tuna is a very popular high-value product and is one of the primary species targeted in the WCPO. Due to high demand and the exponential growth of fishing capacity, bigeye tuna stocks have been continually declining over the past decade, similar to other high-value predatory species. The most recent stock assessment has officially classified bigeye in the WCPO as experiencing overfishing and approaching an overfished state, with total spawning and biomass having declined to about half of their initial levels in the mid-1970s. Though the majority of adult bigeye tuna in the WCPO is targeted and harvested by longline fleets originating from across the Pacific, the past 30 years has seen an exponential increase in the capacity of purse seine fleets due to advancements in technology, such as the development of fish aggregating devices, which is significantly contributing to a reduction in bigeye tuna biomass through the incidental catch of juveniles. Both longline fisheries and purse seine fisheries operating in the WCPO are under the jurisdiction of the Western and Central Pacific Fisheries Commission, and all bigeye tuna caught in the WCPO is managed as one stock, regardless of the landing location or gear deployed.
Hawaii’s longline fleet have little to no direct interaction with (or influence over) decisions made in this policy arena.

Figure. 2.1 Map of the Study System Identifying the Range of Hawaii’s Longline Fleet. Longline fishers are restricted from fishing within 50-75nm of Hawaii’s coastline and typically fish both within, and outside of the United States’ Exclusive Economic Zone (adapted from Barnes-Mauthe et al. 2012, Barnes-Mauthe et al. 2013).

2.2 Hawaii’s Longline Fishery Information Sharing Network

From May 2011 – January 2012, I led an effort to collect detailed data on information sharing among Hawaii’s longline fishers, which is described in detail in Barnes-Mauthe et al. (2012, 2013). The data was collected via a structured survey that asked fishers to identify individuals that they commonly shared information with about fishing that they considered valuable to their fishing success. The survey was targeted to capture the complete information sharing network of all primary decision makers, defined as vessel owners and captains (and owners who also
captain their vessel, or ‘owner/operators’), associated with all active vessels in Hawaii’s longline fleet during the time of data collection.

The survey was employed using face-to-face interviews in the preferred language of each respondent. Respondents were first asked whether or not they frequently discuss or share valuable information regarding different aspects of fishing with other stakeholders in the fishery. Respondents were then asked to identify information sharing relationships with up to ten individuals. Subsequently, respondents disclosed which information sharing topic(s) were discussed with each actor from a predetermined list of topics identified by key informants as important for both long-run and short-run decision making. Short-run information sharing topics included fish activity (i.e., “what the fish are doing”), site catch/set location (where the fish are), bycatch (which is preferably avoided), and weather. Long-term information sharing topics included vessel technology, hiring of captain or crew, fishery regulations, and gear maintenance. Respondents often named other fishers as important for information sharing, but also identified a number of industry leaders and government/management officials. Respondents were also prompted to consider relationships that they had with individuals from other ethnic backgrounds.

Though official records indicate there were 129 active vessels with permits during 2011, only 121 were observed at least once in port in Honolulu throughout the nine months spent in the field. Information obtained from informal discussions with respondents suggested that the difference in permitted vessels versus vessels observed during data collection could be attributed to vessels being sold during the year (3 total, according to informal reports), fishers going out of business (3 vessels according to informal reports), and vessels fishing in other fisheries (2 according to informal reports). According to official records, conversations with respondents, and those nominated in the resulting network, I estimate there were approximately 159 primary decision makers associated with the 121 observed vessels (accounting for all captains, owners, and owner-operators), who are referred to here as ‘fishers.’

With a response rate of over 90%, I was able to explicitly map the information sharing social network structure of nearly all primary decision makers associated with HLF vessels, which is presented graphically in Figure 2.2. In total, 145 fishers associated with 112 vessels participated in the survey. Of the 159 total fishers, 59 were identified as E-A, 26 as K-A, and 74 as V-A, of which 51, 24, and 70 participated as respondents, respectively. Surveys from two individuals were dropped due to inadequate information (1 E-A and 1 K-A fisher), resulting in a total of 143
respondents (90%) from 112 vessels (93%). The resulting information sharing network includes 179 nodes (159 of which are fishers), 895 ties, 250 reciprocal ties, a mean geodesic distance of 4.158, an average degree of 8.556 network neighbors, and one weakly connected component.

![Graphical Depiction of Hawaii's Longline Fishery Information Sharing Network](image)

**Figure 2.2 Graphical Depiction of Hawaii’s Longline Fishery Information Sharing Network.** Each shape (i.e., node) represents an actor in the network, and the lines (i.e., edges) connecting them represent their information sharing relationships, or ties. 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 that they have the shortest path lengths to, while also separating nodes which may overlap in the network graph. Adapted from Barnes-Mauthe et al. (2013).

Described in detail in Barnes-Mauthe et al. (2013), the network exhibits a strong homophily effect along ethnic lines, where communication within ethnic groups is significantly more extensive than between groups. This effect has a substantial impact on the overall structure of information sharing networks in the fishery. Each ethnic community of fishers also has a unique network structure (Barnes-Mauthe et al. 2013). Specifically, the V-A and K-A communities appear to have a bonding network structure, while the E-A community has a bridging network.
structure. Bonding network structures involve strong social ties within groups of similar-minded individuals often characterized by dense, heavily localized networks (Grafton 2005), which have been found to increase trust and cooperation among actors (e.g. Granovetter 1985, Coleman 1990, Pretty and Ward 2001, Hahn et al. 2006). Higher levels of trust among actors can provide incentives to cooperate. Trust can be especially important in marine fisheries because it encourages individual fishers to observe rules, standards, and sustainable practices, which can decrease externalities for individual fishers (Grafton 2005, Barnes-Mauthe et al. 2013). In contrast, bridging network structures characterize weaker social bonds across slightly similar, but distinct groups or social networks (Grafton 2005). Though bridging ties are often weaker than bonding ties, they have the ability to link heterogeneous actors or networks of individuals into a larger network, which can accelerate the flow of diverse information and allow individuals greater access to external resources (Cróna and Bodin 2006, Hahn et al. 2006, Newman and Dale 2007, Bodin and Cróna 2009, Ramirez-Sanchez and Pinkerton 2009, Sandström and Rova 2010, Barnes-Mauthe et al. 2012, Barnes-Mauthe et al. 2013).

The average number of ties identified for each individual fisher also differs along ethnic lines. Fishers in the V-A community have a mean of 15.52 ties per individual; while E-A fishers have mean of 8.79 ties per actor, and K-A fishers have a mean of 7.30 ties per individual. Moreover, the number of potentially powerful actors and trusted industry leaders connected or embedded within the social networks of each ethnic community also differs, which can be conceptualized as the level of linking ties or cross-scale linkages. Linking ties refer to social bonds that span different hierarchical levels or dissimilar groups, such as ties between resource management officials and resource users (Grafton 2005, Barnes-Mauthe et al. 2013). Linking ties to government agencies and/or industry leaders may be vital in influencing individual fisher’s economic outcomes because they can provide access to information on technological innovations or updated scientific knowledge (Barnes-Mauthe et al. 2013).

The results of this previous work (i.e., Barnes-Mauthe et al. 2013) successfully mapped the information sharing network structure of Hawaii’s longline fishers. It also and identified the important role of ethnic differences in mediating the flow of information. This initial work thus served as a platform to launch the inquires in this dissertation, where is it hypothesized that ethnic diversity is an important factor mediating the role of social interaction on fishery-related social, ecological, and economic outcomes.
References


Chapter 3

WHAT DETERMINES SOCIAL CAPITAL IN A SOCIAL-ECOLOGICAL SYSTEM?
INSIGHTS FROM A NETWORK PERSPECTIVE

Abstract

Social capital is an important resource that can be mobilized for purposive action or competitive gain. The distribution of social capital in social-ecological systems can determine who is more productive at extracting ecological resources and who emerges as influential in guiding their management, thereby empowering some while disempowering others. Despite its importance, the factors that contribute to variation in social capital among individuals have not been widely studied. We adopt a network perspective to examine what determines social capital among individuals in social-ecological systems. We begin by identifying network measures of social capital relevant for individuals in this context, and review existing evidence concerning their determinants. Using a complete social network dataset from Hawaii’s longline fishery, we employ social network analysis and other statistical methods to empirically estimate these measures and determine the extent to which individual stakeholder attributes explain variation within them. We find that ethnicity is the strongest predictor of social capital. Measures of human capital (i.e., education, experience), years living in the community, and information sharing attitudes are also important. Surprisingly, we find that when controlling for other factors, industry leaders and formal fishery representatives are generally not well connected. Our results offer new quantitative insights on the relationship between stakeholder diversity, social networks, and social capital in a coupled social-ecological system, which can aid in identifying barriers and opportunities for action to overcome resource management problems. Our results also have implications for achieving resource governance that is not only ecologically and economically sustainable, but also equitable.

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2 This chapter has been published in the journal Environmental Management. The manuscript was led by primary author Barnes, and is reprinted here with the permission of all co-authors. Acronyms, the study system section, and figure and table numbers were adjusted to align with the organization of this thesis. The full citation is: Barnes-Mauthe, M., Gray, S.A., Arita, S. Lynham, J. and P.S. Leung. 2014. What determines social capital in a social-ecological system? Insights from a network perspective. Environmental Management 55(2):392-410.
3.1 Introduction

Social networks, and the patterns of relationships between individuals and groups they comprise, are intimately tied to the notion of social capital. Though there is some debate over the definition and operationalization of the term (Dasgupta and Serageldin 2000, Portes and Landolt 2000, Durlaf 2002), social capital is generally considered a multidimensional concept that incorporates diverse social phenomena such as trust, reciprocity and exchange, norms, and networks of interpersonal relationships (Bourdieu 1986, Coleman 1988, Woolcock and Narayan 2000, Putnam 2001, Sabatini 2009). Often defined by its function (Coleman 1990), the capital analogy captures the idea that social bonds, and the resources embedded within them, comprise an important asset that can be leveraged for individual or collective gain (Bourdieu 1986, Coleman 1990, Lin 1999a, Woolcock 2001, Burt 2005).

Social capital can facilitate social mobility and provide access to resources, e.g., employment and education (Granovetter 1973, Bourdieu 1986, Coleman 1988). In times of crisis, social capital can be a means of social support (Wellman and Frank 2001). Social capital has also been shown to lower transaction costs and facilitate cooperation and collaboration by building trust, encouraging reciprocity and exchange, and enabling the establishment of common rules, norms, and sanctions (Coleman 1988, Fukuyama 1995, Putnam 1995, Pretty 2003, Ostrom and Ahn 2009). When and how social capital facilitates collective action toward sustainable resource management has thus become an important research focus (e.g. Ostrom 1990, Pretty and Ward 2001, Adger 2003, Pretty 2003, Grafton 2005, Sekhar 2007, Gutiérrez et al. 2011).

At its core, social capital is an inherent property of social relationships (Woolcock 2001, Lakon et al. 2008), residing in networks between individuals and communities (Portes 1998, Adger 2003). Social network concepts and methodologies thus provide a useful mechanism for operationalizing social capital (Borgatti et al. 1998, Lakon et al. 2008), and have begun to be adopted by scholars analyzing natural resource management and conservation issues. Bodin and Crona (2008) analyzed community social capital among Kenyan fishers using network characteristics to help explain overexploitation patterns. Ramirez-Sanchez and Pinkerton (2009) applied social network methods to analyze social capital among seven coastal fishing communities in Baja California Sur, Mexico, to draw implications about their resilience and adaptive capacity. Marin et al. (2012) used a network approach to study the relationship between social capital among fisher organizations and co-management performance. Garcia-
Amado et al. (2012) applied a social network perspective to explore the linkages between social capital and collective action in a Mexican forest community.

As these examples illustrate, research examining social capital from a network perspective in social-ecological systems (SESs) has primarily conceptualized it as a collective asset analyzed at the community, or group level. Yet many social capital scholars argue that it is equally important at the individual actor level (Bourdieu 1986, Coleman 1990, Burt 1992, Borgatti et al. 1998, Lin 1999a, Burt 2000). Akin to classical social resource theory (e.g., Lin 1986) and structuralist position theory (Wellman 1988), proponents of this view contend that social relationships comprise an important resource that can be accessed or mobilized for purposive action (Lin 1999a) or competitive gain (Burt 2000), and an actor’s location in the structure of a social network can facilitate or constrain their opportunities for action (Bourdieu 1986, Coleman 1990, Lin 1999a, Burt 2000). Drawing heavily from the work of Granovetter (1973, 1983, 1985, 2005), Burt (1992, 1997, 2000, 2005), Lin (1999a, 2001, 2001), Wellman (2001) and others, from this perspective social capital is typically assessed by gauging the nature and extent of an individual's interpersonal ties or their structural position within a social network (Borgatti et al. 1998, Burt 2000, Sabatini 2009), which has at times been referred to as ‘network capital’ (Wellman and Frank 2001), ‘social network capital’ (Fafchamps and Minten 2002), the ‘structural component’ of social capital (Sabatini 2009), or simply social capital (Burt 1997, Borgatti et al. 1998, Lin 1999a). This approach is pervasive in the economic and organizational sciences, which has provided strong evidence that social capital, assessed explicitly at the individual level using network concepts and methodology, can be an important determinant of socioeconomic outcomes and agency (Fafchamps and Minten 2002, Jackson 2008, Mihaly 2009, Wu et al. 2009, Greve et al. 2010, Lancee 2010). Acknowledging the multidimensionality of the concept, we refer to this conceptualization simply as social capital throughout the rest of this paper.

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3 Though Marin et al. (2012) applied an ego-network approach, identifying the ties of fisher organization leaders, their analysis was focused on social capital implications for the organizations, rather than the individual actors.

4 The disagreement about whether social capital accrues at the individual level, the group level, or both is discussed in detail by Portes (1998) and Borgatti et al. (1998). Burt (1997, 2000, 2005) and Lin (1999a) are arguably the most heavily cited proponents of social capital being assessed at the individual level, while Putnam (2001) famously describes social capital at the level of whole communities and even countries. Following Burt (1992, 1997, 2000, 2005), Lin (1999a, 2001, 2001), Wellman (2001) and many others, our study focuses on social capital at the individual level analyzed from a network perspective. However as the two meanings of social capital (i.e., collective vs. individual benefit) are highly related, we also follow the view that social capital accrues to, and is important for, both individuals and communities (see, Narayan and Pritchett 1999, Fafchamps and Minten 2002, Adger 2003).
The focus of this study is to understand variation in social capital among actors in SESs. SESs often contain a diversity of human stakeholders embedded in social networks (Barnes-Mauthe et al. 2013). Social capital among actors can be important in these settings because those with a greater extensity (or diversity) of ties and advantageous network positions can have considerable advantages in terms of extracting ecological resources and influencing their management. Recent research in natural resource systems has indeed indicated that an actor’s position in a social network and the nature and extent of their ties can affect their ability to access critical information and resources, to exert power and influence over others, and to facilitate collaboration between divergent groups of actors (see Bodin and Crona 2009, Bodin and Prell 2011, and the references therein). The pattern or structure of relationships among stakeholders can also govern who emerges as influential (Crona and Bodin 2006, Bodin and Crona 2008, Crona and Bodin 2010) and economically productive (Mueller et al. 2008, Turner et al. 2014), thereby empowering some while disempowering others. Using a network perspective to understand the level and distribution of social capital among individual stakeholders can thus help to identify barriers and opportunities for action to overcome resource management problems, and can provide insight into achieving equitable management outcomes – an increasingly important goal of sustainable resource governance (Bebbington and Perreault 1999, Brooks 2010, Halpern et al. 2013).

Though it has been identified as an important area for empirical inquiry (Bodin and Crona 2009), relatively few studies have systematically investigated who is more prone to having beneficial ties and occupying advantageous network positions in SESs (but see Maiolo and Johnson 1988, Bodin and Crona 2008, Ramirez-Sanchez 2011b), and none have tested the potential effect of ethnic diversity. With increasing globalization and immigration the composition of stakeholders in natural resource systems is becoming more diverse, particularly in the U.S., yet natural resource management has historically emphasized ‘users’ without considering issues pertaining to racial and ethnic diversity (see Schelhas 2002). Ethnic diversity can cause social fragmentation, low levels of trust across groups, and can produce differences in social structures underlying resource use (Portes and Sensenbrenner 1993, McPherson et al. 2001, Alesina and La Ferrara 2002, Schelhas 2002, Baerveldt et al. 2004, Ruttan 2006, Barnes-Mauthe et al. 2013). How ethnic diversity might interact with other attributes to contribute to variation in social capital among individuals in SES is therefore an important empirical question.
In this paper, we adopt a network perspective to examine what determines social capital among individuals in SESs. Do stakeholder attributes influence social capital? What is the effect of ethnic diversity in this context? Shedding light on these questions can help us to understand why some individuals are more successful than others at accessing information and resources in natural resource systems, which can be a crucial determinant of human behavior (Marsden and Friedkin 1993). Recognizing who is more prone to occupy influential network positions in SESs can also help resource managers in identifying effective change agents and potential partners for collaborations (Bodin and Crona 2009, Valente 2012).

To understand these relationships, we begin by identifying network measures of social capital that are relevant for individuals in this context, and review the existing evidence concerning their determinants. Using a complete social network data set from Hawaii’s ethnically diverse longline fishery, we then employ social network analysis (SNA) and other statistical methods to empirically estimate these measures and determine the extent to which individual stakeholder attributes can explain variation within them. We conclude by offering an interpretation of our results and what they imply for sustainable, and equitable, resource governance in Hawaii and beyond.⁵

3.1.1 Network Measures of Social Capital

SNA offers a variety of sociometric measures that can be used as indicators of social capital (Borgatti et al. 1998). SNA is a quantitative methodology that employs graph theory and sociograms to analyze and visualize social relationships (Wasserman and Faust 1994), where nodes in the graph represent the actors (or sometimes other observations of interest, such as organizations), and the edges or lines between them represent their relationships, or ties. Because there are different ways that being connected in networks can be beneficial, the most appropriate network measures of social capital will depend on the context and the nature of the ties that comprise the network, particularly considering not all ties are positive in nature (Borgatti et al. 1998, Lakon et al. 2008, Sabatini 2009). Here we focus on measures that capture benefits

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⁵ Though we ground our analysis in the theory of social capital following the work of Burt (1992, 1997, 2000, 2005), Lin (1999a, 2001, 2001), Wellman (2001) and others, it is important to keep in mind that the precise definition of social capital is often ambiguous, if not contested (Dasgupta and Serageldin 2000, Portes and Landolt 2000, Durlaf 2002). Thus an analysis of the broader concept of social capital comprised of diverse social phenomena might also explicitly measure aspects of trust, norms, and reciprocity. It is also important to note that the network effects we discuss hold independent of the social capital framework.
in information sharing networks, a commonly studied network type in resource management settings (e.g., Crona and Bodin 2006, Prell et al. 2009, Ramirez-Sanchez and Pinkerton 2009, Barnes-Mauthe et al. 2013). Information is an important asset for stakeholders in SESs (Fafchamps and Minten 2002, Dreyfus-Leon and Gaertner 2006), and being well or strategically connected in these networks has been shown to have economic advantages (Mueller et al. 2008, Turner et al. 2014) and benefits of influence in driving system outcomes (see Bodin and Crona 2009 and the references therein). Evidenced by their theoretical foundations and historical use, in this context measures of tie strength, network prominence, and opportunities for brokerage capture key aspects of social capital (Burt 1992, Borgatti et al. 1998). Focusing on the most prominent, we summarize several of these measures in Table 3.1 and describe them in the following paragraphs, beginning with tie strength.6

*Tie strength* refers to the intensity of the relationship between two actors (Table 3.1), and can be conceptualized in different ways. Granovetter (1973:1361) describes tie strength as a "combination of the amount of time, the emotional intensity, the intimacy (mutual confiding) and the reciprocal services which characterize the tie." Strong ties generally facilitate information exchange (Festinger 1963) and have been shown to positively affect the generation of trust (Krackhardt 1992), the transfer of complex knowledge (Reagans and McEvily 2003), and individual productivity (Abbasi et al. 2011). The theoretical foundations concerning the benefit of strong ties is analogous to the concept of bonding social capital (Grafton 2005). Bonding social capital is a key source of social support and provides a sense of identity and belonging (Woolcock and Narayan 2000). In the context of natural resource governance, bonding ties can enhance mutual learning, the sharing of resources and advice, and enhance trust (Bodin et al. 2006, Prell et al. 2009). In contrast, there is evidence that weak ties can be an important asset in certain settings, e.g., on the job market (Granovetter 1973, Granovetter 1983) and in accessing information at different scales (Friedkin 1982), though these ties are typically more associated with bridging or linking social capital because they cross social divides and link people together at different hierarchical levels (Grafton 2005). Because of their bridging/linking role, weak ties are argued to increase adaptability and social and ecological resilience to environmental change (Newman and Dale 2004, Prell et al. 2009).

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6 This list is certainly not meant to be exhaustive. For a more exhaustive list of potential network measures of social capital, readers are referred to Borgatti et al. (1998).
Network prominence is typically captured by the concept of centrality. Network centrality refers to the position one holds in a network which can indicate power, prominence, or influence (Freeman 1979) and generally captures the volume of benefits available to an individual through their ties (Burt 1992). Several centrality measures have been developed by social network analysts to capture varying conceptualizations of what it means to be prominent or centrally located in a network (see Freeman 1979, Bonacich 1987, Friedkin 1991). Some of the more popular ones which have been found to be important for influencing social and economic outcomes are degree, eigenvector, and betweenness centrality (Table 3.1). Though betweenness centrality, discussed below, is perhaps better conceptualized as a form of bridging or brokerage rather than a classic measure of network prominence.

Table 3.1 Individual Level Network Measures of Social Capital.¹

<table>
<thead>
<tr>
<th>Network Measure</th>
<th>Description</th>
<th>Social Capital Advantage</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>TIE STRENGTH</strong></td>
<td>Tie strength (Festinger 1963, Haythornthwaite 1996)</td>
<td>The intensity of the relationship between two actors.</td>
</tr>
<tr>
<td><strong>NETWORK PROMINENCE</strong></td>
<td>Degree centrality (Freeman 1979)</td>
<td>A measure of local centrality capturing the number of contacts an actor has in a network.</td>
</tr>
<tr>
<td></td>
<td>Eigenvector centrality² (Bonacich 1972)</td>
<td>A measure of global centrality, capturing how well connected an actor is, in addition to how well connected the actors they have ties to are.</td>
</tr>
</tbody>
</table>
**Betweenness centrality** (Freeman 1979) Measures the number of times an actor falls on the shortest path length between two others who are not directly connected. Betweenness centrality offers access to diverse information and resources and the ability to control their flow (Borgatti et al. 1998, Burt 2002, Bodin et al. 2006). Betweenness centrality influences resource exchange, has been positively correlated with trust (Tsai and Ghoshal 1998), and can indicate influence in SESs (Bodin et al. 2006, Bodin and Crona 2009).

**Efficiency** (Burt 1992, Burt 2002) A measure of an optimized network that idealizes non-redundant contacts, i.e., ties that link unconnected network groups or portions of the network. Derived from the theory of structural holes (Burt 1992), efficiency gives actors opportunities to yield information access and control benefits by acting as a broker between otherwise unconnected network groups. Associated with bridging social capital, efficiency can be an important factor influencing performance (Abbasi et al. 2011).

**Bridging, or heterogeneous ties** (Borgatti et al. 1998, Grafton 2005, Bodin and Crona 2009) Ties that bridge different social groups at similar scales (e.g., ties between heterogeneous resource user groups). Individuals whose ties bridge diverse social groups gain access to diverse information and resources, which increases their opportunities for action (Burt 2000). A form of bridging social capital, bridging ties can enhance innovative capacity, resilience, and adaptability (Newman and Dale 2004, Bodin and Crona 2009, Prell et al. 2009).

**Linking ties** (Woolcock 2001, Grafton 2005) Ties that link actors at different hierarchical levels (e.g., ties between resource users and resource managers). Linking ties provide access to diverse information and resources at different scales (Grafton 2005) and can enable actors to gain influence in decision-making processes (King 2000). Linking ties are associated with linking social capital (Grafton 2005).

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**Degree centrality** is a simple measure of local centrality which measures the number of edges (i.e., ties) a node has in a network. Actors with a high degree centrality have more contacts, and thus have increased opportunities and alternatives for sharing and receiving information (Hanneman and Riddle 2005). High degree centrality scores can also give actors greater influence and power over information transmission (Freeman 1979), and have proven to be an important asset influencing economic productivity (Greve et al. 2010, Abbasi et al. 2011). Initially suggested by Bodin et al. (2006) due to its correspondence with the theory of social entrepreneurship (Westley and Vredenburg 1997), degree centrality can also be vital for identifying highly connected, key stakeholders in SESs who may be well positioned to foster (or impede) collaboration among others toward more sustainable outcomes (Crona and Bodin 2006, Bodin and Crona 2008, Crona and Bodin 2010, Bodin and Crona 2011, Prell et al. 2011, Ramirez-Sanchez 2011b). In a directed network, where information on the direction of the tie (either outgoing or incoming) is available, degree centrality can be distinguished by two
measures: *indegree*, representing ties coming in to an actor; and *outdegree*, representing ties going out from an actor. This distinction can be important because if an actor has a high indegree, then a high number of individuals are likely seeking them out, thus indicating their prominence or importance in the network (Hanneman and Riddle 2005). On the other hand, actors with high outdegree are able to exchange with many others and potentially spread awareness of their views, and are therefore thought to be influential (Hanneman and Riddle 2005).

*Eigenvector centrality* is a centrality measure developed by Bonacich (1972) which is based on the idea that an actor’s centrality in a network is based not only on how central they are, but also on how central the actors they have ties to are. In contrast to degree centrality, which captures local centrality, eigenvector centrality places emphasis on actors’ reach in the overall global network. For example, an actor who is connected to many others that are themselves well-connected throughout the extent of the network would have a high eigenvector centrality (Hanneman and Riddle 2005). Eigenvector centrality has been shown to be an important factor influencing organizational effectiveness (Moore et al. 2003), firm and student performance (Mihaly 2009, Larcker et al. 2010), and scholarly productivity (Abbasi et al. 2011), and may be one of the most important network measures for information diffusion (Banerjee et al. 2012). Because of its relationship with social influence, eigenvector centrality has also been employed in a resource extraction setting to identify key individuals (Bodin and Crona 2008).

*Betweenness centrality*, developed by Freeman (1979), measures the number of times an actor, or node, falls on the shortest path length between other nodes (actors) in the network. This can be conceptualized as how often an individual might act as an intermediary or broker between others who are themselves not connected, which sets it apart from other classic measures of centrality. In line with the idea of bridging social capital, the measure captures the idea of bridging ties (Bodin and Crona 2009) that connect disparate groups and provides access to diverse knowledge and resources, thereby enhancing the quality of benefits available to an actor (Granovetter 1973, Burt 1992, Burt 2002). Betweenness centrality has been shown to be a significant factor influencing resource exchange, in addition to being positively correlated with higher levels of trust (Tsai and Ghoshal 1998). Along with degree centrality, it is also a principal measure recognized as important for identifying potentially powerful actors in natural resource systems (Bodin et al. 2006), and has been used as such in several studies (e.g., Mailo and Johnson 1998, Bodin and Crona 2008, Prell et al. 2011).
In addition to being centrality located in a network, being strategically located can also be beneficial because it offers opportunities for brokerage (Burt 2000, 2005). This concept is exemplified through the measure of efficiency (Table 3.1), which stems from Burt’s (1995) theory of brokerage or structural holes. Structural holes in a network refer to an actor that connects disparate groups, which if removed, would fragment the network into two or more sub-networks. Somewhat similar to the bridging role captured by betweenness centrality, actors occupying structural holes in a network have the ability to yield information and control benefits by acting as a bridge between otherwise unconnected groups of actors (Burt 1992). Efficiency, which was recently shown to be an important factor influencing individual productivity (Abbasi et al. 2011), is a measure of an optimized network building on the structural holes theory that idealizes non-redundant contacts. Efficiency captures the idea that having ties to others who are not connected amongst themselves yields access and control benefits because they facilitate the flow of, and control over, novel information and resources.

Opportunities for brokerage can also be captured by directly examining tie diversity, or ties that link different types or subgroups of actors, which corresponds to the discussion on weak, bridging ties (Table 3.1) and to what Borgatti et al. (1998) describe as network heterogeneity. In settings where there are closely aligned subgroups or strong homophilic tendencies, where individuals prefer to interact solely with others similar to themselves along some trait or set of traits, information and resources often become highly centralized and homogenous within groups (McPherson et al. 2001). Individuals who effectively span these groups with a diversity of ties to different types of actors are much more likely to have access to diverse information and resources, thereby enhancing the quality of benefits available to them and increasing their opportunities for action (Burt 1992). Bridging ties are a form of bridging social capital and have been established as an important resource in SESs, in part due to their ability to enhance innovative capacity (Bodin and Crona 2009), resilience, and adaptability to environmental change (Newman and Dale 2004, Prell et al. 2009). Linking ties, sometimes referred to as cross-scale linkages, which link actors at different hierarchical levels (e.g., a tie between a fisher and a fishery manager or scientist), function in a similar manner (Table 3.1). Linking ties are analogous to linking social capital and can be particularly beneficial in the context of SESs because they provide stakeholders access to critical scientific information and technological innovations (Grafton 2005). Linking ties to formally powerful actors can also empower resource users by facilitating influence in decision-making processes (King 2000).
3.1.2 Antecedents?

Though evidence detailing the effects of network measures of social capital on socioeconomic outcomes is profuse across a range of disciplines, less information exists on their antecedents. In the context of SESs a handful of inquiries provide some insight into stakeholder attributes that may be important, particularly for measures of network centrality and brokerage. In their analysis of fisher networks in the Southeast U.S., Mailo and Johnson (1998) found that commercial mackerel and shrimp fishers with higher degree centrality scores tended to have more organizational affiliations and subscriptions to information outlets, indicating a propensity to actively seek information. Among commercial mackerel fishers (excluding shrimp fishers), years in the community and education were also important predictors (Mailo and Johnson 1998). In a Mexican forest community, Garcia-Amado et al. (2012) found an inequity in degree centrality between individuals with different titles or roles (i.e., landholders vs. non landholders) and levels of activity in a local decision-making assembly. In a rural fishing community, Bodin and Crona (2008, 2011) found degree and betweenness centrality and brokerage in knowledge sharing networks to be correlated with occupation and tribe. The role of individual stakeholders (e.g., conservationist vs. agriculturalist) was also found to be related with degree and betweenness centrality in an English National Park by Prell et al. (2009, 2011). Among Mexican small-scale fishers, Ramirez-Sanchez (2011b) found that years living in the community was significantly related to degree centrality, while experience fishing was also important in some communities.

Though previous research has not formally assessed the effect of ethnic diversity on individual social capital in a SES, the evidence concerning tribal affiliation among Kenyan fishers (Bodin and Crona 2008, Bodin and Crona 2011), which is a form of socio-cultural identity, supports that it may be an important factor. Ethnic diversity is known to cause divides among groups with different ethnic affiliations, labeled a form of ‘homophily’ in the network literature (McPherson et al. 2001), which can lead to fragmentation (Alesina and La Ferrara 2002). Homophily, the phenomena of individuals preferring to interact with others similar to themselves, is a well-known driver of network ties (McPherson et al. 2001, Moody 2001), and can produce fundamental differences in social structures underlying resource use (Schelhas 2002, Barnes-Mauthe et al. 2013). Thus, in social networks plagued by ethnic homophily, individual levels of social capital are likely to be influenced by the greater global network structure of their ethnic community.
Taken together, this evidence from a diverse range of SESs (though limited) suggests that, independently, the role of an individual (i.e., occupation or title), their socio-cultural identity (i.e., tribe, ethnicity, etc.), education, experience, years living in the community, activity in organizations (i.e., assemblies/meetings/etc.), and propensity to seek information may be important indicators of social capital among individual stakeholders. With a few omissions, much of this corresponds to empirical evidence from other settings. For example, membership or activity in organizations, but also personalities or attitudes toward sociability, have been found to be correlated with network measures of social capital in organizational settings (Burt et al. 1998, Klein et al. 2004). An individual's propensity to seek information may to some extent be captured by their attitude toward sociability. There also exists substantial evidence in the sociology and management science literature suggesting social capital is often correlated with aspects of human capital, which represents the knowledge, skills, and talents accumulated over time by an individual (Becker 1964, Coleman 1988, Lin 1999b, Lin and Huang 2005, Helliwell and Putnam 2007). Measures of human capital often include an individual's title or role, their level of experience, and education (Becker 1964, Schultz 1971, Lin and Huang 2005). Lastly, network formation theory suggests that as people enter social networks, they tend to disproportionately form ties with those who are already well connected (Price 1976, Barabási and Albert 1999), which adds further support for years in the community being a predictor, while also suggesting that age may be important.

Building on this theoretical and empirical evidence, we use the remainder of this paper to simultaneously test the potentially competing effects of these individual attributes on social capital in a SES. Specifically, we test whether ethnicity, title (i.e., role), age, education, years living in the community, experience, information sharing attitude (as a proxy for sociability), and organization activity are significant predictors using an information sharing network from HLF. This research is unique in that it leverages a complete social network dataset; i.e., it covers the population of resource users; and simultaneously, statistically tests the potentially competing effects of several stakeholder attributes on seven network measures that represent different aspects of social capital. Ultimately, this research will aid us in understanding who within a social network is more prone to forming information sharing ties and occupying advantageous network positions in resource extraction settings, and contribute to uncovering the determinants of social capital in SESs. This research is also practical in that it will provide managers, practitioners, and others interested in collective behavior change across diverse resource user
3.2 Methods

3.2.1 Data

We leverage a complete social network dataset on the population of resource users from HLF collected in 2011-2012 by Barnes-Mauthe et al. (2013). The dataset includes network data on information sharing in addition to socio-demographic data collected from primary decision-makers, defined as vessel owners and captains (some of whom both own and operate their vessel). The entire dataset includes information from 145 fishers out of an estimated total of 159, five of which are considered isolated and not generally active in the HLF (Barnes-Mauthe et al. 2013). Of the 145, socio-demographic data on five fishers was incomplete. They were therefore excluded from this analysis, leaving a usable sample of 140 fishers. To identify network ties, respondents were asked to nominate up to 10 individuals with whom they commonly shared information that they felt was valuable for their success in the HLF. Respondents often nominated other vessel owners and captains, but also nominated additional actors, such as government/management officials and industry leaders (e.g., owners of fishing supply stores or fishing organization representatives). When accounting for all actors identified by respondents as important for information sharing, the final network included 179 individuals, which is displayed graphically in Fig. 2.2. The network exhibits strong homophily along ethnic lines, with fishers primarily sharing information within their ethnic group (Barnes-Mauthe et al. 2013). Further information on the study system and network data are provided in Chapter 2.

3.2.2 Selected Measures of Social Capital

We test the factors that contribute to average tie strength, indegree centrality, outdegree centrality, betweenness centrality, efficiency, and two measures that capture bridging and linking ties, which we refer to as bridging factor and linking factor. We initially sought to also include eigenvector centrality, but found that it was heavily influenced by the size of V-A group of fishers coupled with the strong homophily effect (S. Borgatti, personal communication). Drawing from their theoretical and empirical foundations, higher scores of all tested measures are considered to represent greater levels of social capital. This is particularly the case in this
context, as the value of information in competitive fisheries has been well documented (Mangel and Clark 1983, Rudd 2001, Salas and Gaertner 2004, Dreyfus-Leon and Gaertner 2006, Gezelius 2007).

Tie strength can be measured in several ways. Kinship, intimacy, provision of reciprocal services, frequency of contact, and duration of the association, or combinations of these, have all been used as measures of tie strength (Haythornthwaite 1996). Burt suggests that empirical measures of ties strength include two principal factors, emotional closeness/tie intimacy and frequency of contact (Burt 1992). In the SESs literature, a hierarchy has been identified in relation to tie strength, with kinship ties being the strongest, followed by friendship ties, and then acquaintance ties (Ramirez-Sanchez 2011a). We thus determined tie strength by considering tie intimacy (family member > friend > professional acquaintance), frequency of interaction (1-3 times per week > 1-3 times per month > 1-3 times per year), and respondent’s self-selected tie strength (very strong > strong > weak > very weak). Each attribute level was assigned a number from 1-4, where higher numbers represented stronger connections (e.g., family member = 3, friend = 2, acquaintance = 1), and then all attribute levels were summed to provide the weight of each link in the network. Average tie strength was then simply calculated as the sum of each actor’s tie weights (including all indegree and outdegree ties) divided by their total number of ties.

We used UCINET 6.0 (Borgatti et al. 2002) to calculate all standard network metrics for individual HLF fishers, including efficiency and normalized measures of indegree, outdegree, and betweenness centrality. Centrality measures were normalized based on the total possible in the network. Efficiency is a standard measure included in the structural holes feature of UCINET. Formulas for each of these measures are included in the Supplementary Material.

---

7 Though there is some debate over whether strong or weak ties are more beneficial (Granovetter 1983) and thus better represent social capital, weak ties are known to hamper the transfer of complex, tacit knowledge (Hansen 1999), which is essential for understanding and adapting to the conditions in dynamic, complex SESs (Berkes et al. 2003). Weak ties are also less likely to be useful in situations where information is valuable and the costs of providing it are high (Brass et al. 2004), which is typically considered to be the case in competitive fisheries (Wilson 1990, Dreyfus-Leon and Gaertner 2006). Moreover, as argued by Burt (1992), the social capital benefits of weak ties originally described by Granovetter (1973), i.e., access to diverse information and resources at different scales and control over their flow, are more accurately captured by measures that explicitly take into account tie diversity (e.g., ties that bridge/link) and access to structural holes, which we capture through measures of brokerage (i.e., efficiency, bridging and linking factor). The assumption that strong ties are more beneficial in this context for the measure of average tie strength is thus well justified.
Because information and resources may become redundant within ethnic groups in the HLF due to the observed homophily effect, ties that bridge ethnic groups are also likely to embody brokerage advantages (Barnes-Mauthe et al. 2012, Borgatti et al. 1998). To capture this, we used the E-I index function in UCINET 6.0 (Borgatti et al. 2002) to calculate the total number of ties each fisher had that crossed ethnic boundaries, which we termed ‘bridging factor’. Considering that linking ties to different types of actors, in addition to having a variety of linking ties across different types of actors, are also likely beneficial for fishers in different circumstances (Grafton 2005), we conceptualized three separate measures of linking ties for HLF fishers: (1) their number of ties to industry leaders, (2) their number of ties to government/management officials and members of the scientific community, and (3) their total number of linking ties (1 + 2). These three measures had a high positive correlation. A principal component analysis was therefore used to extract a single component score for linking ties. The single component, which we refer to as ‘linking factor,’ accounted for 73.5% of the total variance.

3.2.3 Stakeholder Attributes

Stakeholder attributes are summarized in Table 3.2. Ethnicity captures the three different ethnic groups. For title, each fisher was classified as a vessel owner (“owner”), captain (“captain”), owner who also operates their vessel (“owner/operator”), or vessel owner who can also be classified as an industry leader (“owner/industry leader”). In the present study, owners/industry leaders comprise those that represent other fishers in the management and policy arena through local fishery organizations, those that hold different formal positions in one of these organizations, or those that own a supply store or business that services the majority of Hawaii’s longline fleet. In some cases, owner/industry leaders may concurrently play more than one of these roles. Education was reduced to a two factor variable (high school or less = 0; some college or above = 1).
**Table 3.2 Hawaii’s Longline Fishery Stakeholder Attributes (n = 140).**

<table>
<thead>
<tr>
<th>Description</th>
<th>E-A</th>
<th>K-A</th>
<th>V-A</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>N</strong></td>
<td>48</td>
<td>22</td>
<td>70</td>
</tr>
<tr>
<td><strong>Title</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Owner</td>
<td>6 (13%)</td>
<td>3 (13%)</td>
<td>16 (23%)</td>
</tr>
<tr>
<td>Captain</td>
<td>26 (54%)</td>
<td>4 (18%)</td>
<td>36 (51%)</td>
</tr>
<tr>
<td>Owner/Operator</td>
<td>7 (15%)</td>
<td>14 (64%)</td>
<td>13 (19%)</td>
</tr>
<tr>
<td>Owner/Industry Leader</td>
<td>9 (19%)</td>
<td>1 (5%)</td>
<td>5 (7%)</td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>None</td>
<td>0 (0%)</td>
<td>1 (5%)</td>
<td>1 (1%)</td>
</tr>
<tr>
<td>Elementary School</td>
<td>0 (0%)</td>
<td>2 (9%)</td>
<td>45 (64%)</td>
</tr>
<tr>
<td>High School</td>
<td>23 (48%)</td>
<td>18 (81%)</td>
<td>9 (13%)</td>
</tr>
<tr>
<td>Some College</td>
<td>19 (40%)</td>
<td>1 (5%)</td>
<td>5 (7%)</td>
</tr>
<tr>
<td>Bachelor’s Degree or Higher</td>
<td>6 (12%)</td>
<td>0 (0%)</td>
<td>10 (14%)</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M</td>
<td>51.38a</td>
<td>57.64</td>
<td>51.30a</td>
</tr>
<tr>
<td>min</td>
<td>25</td>
<td>39</td>
<td>29</td>
</tr>
<tr>
<td>max</td>
<td>72</td>
<td>68</td>
<td>72</td>
</tr>
<tr>
<td>SD</td>
<td>10.91</td>
<td>7.97</td>
<td>9.47</td>
</tr>
<tr>
<td><strong>Experience</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M</td>
<td>30.94a</td>
<td>29.00a</td>
<td>17.04</td>
</tr>
<tr>
<td>min</td>
<td>7</td>
<td>16</td>
<td>1</td>
</tr>
<tr>
<td>max</td>
<td>54</td>
<td>46</td>
<td>29</td>
</tr>
<tr>
<td>SD</td>
<td>10.96</td>
<td>7.94</td>
<td>7.11</td>
</tr>
<tr>
<td><strong>Years in community</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M</td>
<td>14.96</td>
<td>28.27</td>
<td>19.34</td>
</tr>
<tr>
<td>min</td>
<td>0</td>
<td>16</td>
<td>0</td>
</tr>
<tr>
<td>max</td>
<td>67</td>
<td>37</td>
<td>33</td>
</tr>
<tr>
<td>SD</td>
<td>14.79</td>
<td>5.52</td>
<td>5.55</td>
</tr>
<tr>
<td><strong>Info. sharing attitude</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M</td>
<td>7.92a</td>
<td>8.58a</td>
<td>9.51</td>
</tr>
<tr>
<td>min</td>
<td>2.85</td>
<td>5.35</td>
<td>4.45</td>
</tr>
<tr>
<td>max</td>
<td>9.8</td>
<td>9.8</td>
<td>9.8</td>
</tr>
<tr>
<td>SD</td>
<td>1.79</td>
<td>1.44</td>
<td>0.82</td>
</tr>
<tr>
<td><strong>Organization activity</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-member</td>
<td>7 (14%)</td>
<td>1 (5%)</td>
<td>0 (0%)</td>
</tr>
<tr>
<td>Member, not active</td>
<td>21 (44%)</td>
<td>19 (85%)</td>
<td>56 (80%)</td>
</tr>
<tr>
<td>Member, active</td>
<td>11 (23%)</td>
<td>1 (5%)</td>
<td>11 (16%)</td>
</tr>
<tr>
<td>Officer or board member</td>
<td>9 (19%)</td>
<td>1 (5%)</td>
<td>3 (4%)</td>
</tr>
</tbody>
</table>

*aDescribes homogenous subsets using the least significant difference (LSD) & Tukey test at the 0.05 level of significance.

Experience is equal to years of experience fishing. Information sharing attitude is a summed index comprised of two Likert scale questions which asked respondents about their general frequency of information sharing (with anyone) in the HLF (1-3 times per year, 1-3 per month, or 1-3 per week; scaled from 1 to 4), and how valuable they felt information sharing was in general (not important = 1, somewhat important = 2, important = 3, or very important = 4). Organization activity captures the activity level of individuals in local organizations which represent HLF fishers in the management and policy arena, and sometimes help fishers with technical needs. There is one primary organization, the Hawaii Longline Association, to which the majority of HLF
There are also two other organizations, VAK Fisheries and the Hawaii Korean Longline Association. Organization activity captures activity in any of these three organizations, captured as “non-member” (not a member of any), “member, not active”, “member, active”, or “officer/board member,” which identifies those that have, or are currently serving as officers or board members in the organizations.

3.2.4 Statistical Analyses

We investigated a series of General Linear Models (GLMs) on each network measure of social capital, modeled individually, testing for the main effects of all stakeholder attributes. Because network measures are inherently dependent on relations between actors, standard formulas for computing standard errors that rely on the assumption of independence are assumed inadequate (Hanneman and Riddle 2005). We therefore report standard errors and significance levels generated from 1,000 random permutations, which is equivalent to approach used in the regression procedure in UCINET (S. Borgatti, personal communication). We evaluated statistical significance at the 0.01, 0.05, and 0.10 level. All analyses were performed in R and checked for consistency in SPSS Version 22.

3.3 Results

Our results show that ethnicity is a significant predictor for the majority of network measures of social capital (Table 3.3). When accounting for all other factors included in the model, with respect to V-A fishers, E-A and K-A fishers tend to have significantly lower levels of social capital when considering network prominence (i.e., indegree and outdegree centrality). K-A fishers also have a significantly lower level of linking ties than V-A fishers ($\beta = -1.11$, $p < 0.01$). In contrast, when accounting for all other factors included in the models, K-A fishers appear to have a significantly higher average tie strength than V-A fishers ($\beta = 0.58$, $p < 0.01$), while E-A fishers appear to have a significantly higher level of network efficiency ($\beta = 0.07$, $p < 0.01$).

---

8 The majority of HLF fishers sell their fish at the Honolulu Fish Auction, which automatically charges 2 cents per pound of fish to all sellers.
Table 3.3 Model Results. ANCOVA unstandardized parameter estimates from seven individually modeled network measures of social capital.

<table>
<thead>
<tr>
<th>Ethnicity</th>
<th>Avg. tie strength</th>
<th>Norm. outdegree centrality</th>
<th>Norm. indegree centrality</th>
<th>Norm. between. centrality</th>
<th>Efficiency</th>
<th>Bridging factor</th>
<th>Linking factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>E-A</td>
<td>0.07</td>
<td>-1.21***</td>
<td>-3.42***</td>
<td>0.55</td>
<td>0.07***</td>
<td>0.37</td>
<td>-0.38</td>
</tr>
<tr>
<td>K-A</td>
<td>0.58***</td>
<td>-2.48***</td>
<td>-3.09***</td>
<td>-0.61</td>
<td>0.05</td>
<td>-0.03</td>
<td>-1.11***</td>
</tr>
<tr>
<td>V-A</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Title</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Owner</td>
<td>-0.17</td>
<td>-1.14</td>
<td>-2.13</td>
<td>-4.45</td>
<td>-0.11</td>
<td>-3.87</td>
<td>-2.99</td>
</tr>
<tr>
<td>Captain</td>
<td>-0.18</td>
<td>-1.45</td>
<td>-0.98</td>
<td>-4.41</td>
<td>-0.15</td>
<td>-4.45*</td>
<td>-3.73</td>
</tr>
<tr>
<td>Owner/Operator</td>
<td>-0.25</td>
<td>-1.61</td>
<td>-0.04</td>
<td>-4.10</td>
<td>-0.13</td>
<td>-4.16*</td>
<td>-3.57</td>
</tr>
<tr>
<td>Owner/Ind. lead</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<tr>
<td>Education</td>
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<td></td>
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<td>High school or less</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Some college or higher</td>
<td>0.07</td>
<td>0.36*</td>
<td>1.06**</td>
<td>0.74*</td>
<td>0.01</td>
<td>0.61***</td>
<td>-0.12</td>
</tr>
<tr>
<td>Other</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.00</td>
<td>0.01</td>
<td>-0.02</td>
<td>0.01</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Experience</td>
<td>-0.01**</td>
<td>0.01</td>
<td>0.06*</td>
<td>0.04*</td>
<td>0.00</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Years in community</td>
<td>0.00</td>
<td>0.02**</td>
<td>0.00</td>
<td>0.04*</td>
<td>0.00</td>
<td>0.03**</td>
<td>0.01</td>
</tr>
<tr>
<td>Info. sharing attitude</td>
<td>0.03</td>
<td>0.34***</td>
<td>-0.10</td>
<td>0.28*</td>
<td>-0.01</td>
<td>0.06</td>
<td>0.06</td>
</tr>
<tr>
<td>Org. Activity</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-member</td>
<td>0.56*</td>
<td>1.44</td>
<td>-4.63</td>
<td>2.69</td>
<td>0.10</td>
<td>1.92</td>
<td>2.75</td>
</tr>
<tr>
<td>Member, not active</td>
<td>0.16</td>
<td>1.64</td>
<td>-4.20</td>
<td>2.40</td>
<td>0.12</td>
<td>1.92</td>
<td>3.11</td>
</tr>
<tr>
<td>Member, active</td>
<td>0.03</td>
<td>1.34</td>
<td>-2.81</td>
<td>2.99</td>
<td>0.13</td>
<td>2.32</td>
<td>2.99</td>
</tr>
<tr>
<td>Officer or board member</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>R²</td>
<td>0.18</td>
<td>0.55</td>
<td>0.31</td>
<td>0.31</td>
<td>0.22</td>
<td>0.41</td>
<td>0.43</td>
</tr>
</tbody>
</table>

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

This category was used as the reference group.

Having a higher level of education (i.e., some college or above, such as a bachelor’s degree or higher) is also important for several network prominence and brokerage measures. Specifically, it is positively related to outdegree ($\beta = 0.36$, $p < 0.10$), indegree ($\beta = 1.06$, $p < 0.05$), and betweenness centrality ($\beta = 0.74$, $p < 0.10$), as well as bridging factor ($\beta = 0.61$, $p < 0.01$). Experience and years in the community are also important for a range of measures. Specifically, both have a positive effect on betweenness centrality at the same magnitude and level of
significance ($\beta = 0.04$, $p < 0.10$). In addition, experience has a significant, positive effect on indegree centrality ($\beta = 0.06$, $p < 0.10$) but a significant, negative effect on average tie strength ($\beta = -0.01$, $p < 0.05$), while years in the community is significantly, positively related to both outdegree centrality ($\beta = 0.02$, $p < 0.05$) and bridging factor ($\beta = 0.03$, $p < 0.05$). Information sharing attitude is also a significant predictor for betweenness centrality ($\beta = 0.28$, $p < 0.10$) in addition to outdegree centrality ($\beta = 0.34$, $p < 0.01$).

Surprisingly, title and organization activity are only marginally related to one measure of social capital each. Being a captain or owner/operator compared to a vessel owner who is also an industry leader has a significantly negative relationship with bridging factor ($\beta = -4.45$, $p < 0.10$ and $\beta = -4.16$, $p < 0.10$, respectively), while not being a member of any fishery organizations has a positive relationship with average tie strength ($\beta = 0.56$, $p < 0.10$). Finally, age is not a significant predictor of any of the tested measures.

Clearly there are other factors influencing these measures of social capital among resource users in addition to the attributes included in this analysis. Still, our results indicate relatively high explanatory power for some models (Table 3.3). This is particularly the case for outdegree centrality ($R^2 = 0.55$) and the linking ($R^2 = 0.43$) and bridging factor ($R^2 = 0.41$).

### 3.4 Discussion

#### 3.4.1 Effects of Ethnic Diversity

Our results show that ethnicity is the strongest predictor of individual social capital, having effects on measures of tie strength, network prominence, and brokerage (Table 3.3). V-A fishers have more contacts and thus more opportunities for sharing and receiving information than others. V-A fishers also have significantly more linking ties to outside industry leaders and actors in formal positions (such as fishery managers) than K-A fishers. This suggests they have greater access to information at different scales, e.g., information on technological innovation that can increase their efficiency (Grafton 2005), and are more likely have influence in management decision-making (King 2000).

These results are interesting for several reasons. First, sociocultural identity (i.e., tribal affiliation) was also found to be a significant factor influencing network centrality and brokerage in knowledge sharing networks among Kenyan fishers (Crona and Bodin 2006, Bodin and
Coupled with our results, evidence suggesting it may be a driving factor in other natural resource settings as well is mounting. Second, our results in conjunction with previous work (Allen and Gough 2006, Allen and Gough 2007, Barnes-Mauthe et al. 2013, Allen et al. 2014) suggest that the V-A fishing community has characteristics of an ethnic enclave (Portes and Sensenbrenner 1993), and individual V-A fishers may be benefiting from this structure and what is sometimes termed ‘ethnicity as social capital’ (e.g., Zhou 2005). Ethnic enclaves are characterized by a high density of social relations and extensive networking ties that offer immigrants an avenue for economic advancement by creating jobs and opportunities for entrepreneurship (Granovetter 1973, Portes and Sensenbrenner 1993). Residents of ethnic enclaves are typically first generation immigrants with a strong sense of community, history, and culture (Zhou 2005). Creation of ethnic enclaves is suggested to be one way that immigrants cope with the structural conditions associated with resettlement in a foreign country, e.g., linguistic isolation and needing to acquire new labor market skills (Gordon 1964, Zhou 2005).

In our case study, the majority of V-A fishers are first generation immigrants that originally left Vietnam as refugees and ended up in Hawaii after first trying to resettle in several other locations, including the Gulf States of the U.S. (Allen and Gough 2006). Research on V-A immigrants in the Gulf found that the experience of exile and resettlement was formative in shaping the way they interact, resulting in tight family and community relationships which have been positively linked to social and economic development (Moberg and Thomas 1998, Bankston 2004). Existing research specifically suggests that V-A immigrants in the Gulf were able to use their strong social organization, or ‘ethnicity as social capital,’ to survive by securing a strong foothold in the fishing industry (Moberg and Thomas 1998). Our results coupled with previous research (Barnes-Mauthe et al. 2013) and local observations suggest a similar pattern in the HLF. There is indeed strong kinship and solidarity among most V-A fishers, with many of them being related or considered non-traditional family (Allen et al. 2014). Moreover, despite being disproportionately impacted by the Hawaii swordfish fishery closure in 2001, V-A fishers exhibit a high capacity for adaptation, with previous research citing community networks as a primary source of support (Allen and Gough 2006). Even with increasing impacts from stricter regulation over the past decade, there has been a substantial increase in V-A vessel ownership, with V-A fishers now owning a majority of vessels for the first time in the fishery’s history (Barnes-Mauthe et al. 2013).
Though our results show that K-A fishers tend to have stronger ties than V-A fishers, their level of social organization in the fishery, which lacks in network prominence and brokerage (Table 3.3), more closely resembles ethnic isolation rather than an ethnic enclave (Zhou 2005). Research on social capital and ethnicity shows that in isolated immigrant communities, social capital resources are often barely enough to serve survival needs, much less facilitate economic success and mobility (Fernández-Kelly 1995). Previous research on the HLF has found K-A fishers to be generally less satisfied with their job, perceive fishing regulations as more problematic, and feel more marginalized by fishing associations that represent them in the policy arena than others (Allen and Gough 2007, Allen et al. 2014). K-A fishers have also been increasingly exiting the fishery in recent years, often selling their vessels to V-A fishers (Barnes-Mauthe et al. 2013). Our results offer interesting insight into these findings. Deficits in network prominence and brokerage opportunities among K-A fishers indicate a lack of access to basic information and resources that would enable them to innovate and adapt to increased regulation (Newman and Dale 2004, Bodin and Crona 2009, Prell et al. 2009), and suggests they may not possess the relationships necessary to gain influence in the management and policy process (King 2000). Recent research in social psychology also suggests that centrality in social networks (which K-A fishers lack) facilitates a tolerance for a lack of control, and thus increased readiness for change, as well as interpretations of change as controllable once it has occurred, thereby increasing individual adaptive capacity (Vardaman et al. 2012). In other words, a general lack of connectedness in HLF network could be related to K-A fisher’s inability to adapt to regulatory changes and maintain their foothold in the fishery for a variety of reasons. However, there could be several other factors contributing to the exodus of K-A fishers from Hawaii’s longline fleet as well, such as the relative social status of commercial fishers, which may vary across ethnic groups. The relative social status of fishers within ethnic groups may also affect individual fisher’s ability to leverage community resources and support in order to gain influence in the fishery, a topic ripe for future research.

3.4.2 Social Capital and Human Capital

Our results concerning ethnicity also provide insight into the relationship between social capital and human capital. Here, we found that V-A fishers, who generally have less formal education and on average have significantly less experience than others (Table 3.2), tended to benefit from having the social capital characteristics of an ethnic enclave. Education and experience are
key aspects of human capital, which is theorized to have a direct relationship with social capital (Coleman 1988, Brooks 2010). Though social capital has been found to be positively correlated with human capital (Lin 1999b, Lin and Huang 2005, Helliwell and Putnam 2007) and a mechanism by which one can build or use their human capital (Coleman 1988, Burt 1992, Brooks 2010), existing research also suggests that social capital in the form of increased or superior connections can sometimes compensate for a lack of human capital (Coleman 1988, Adler and Kwon 2002). Thus, it may be that due to deficits in human capital, building social capital by way of sharing information more frequently and with a greater number of contacts is perceived as more valuable to V-A fishers, which is supported by the fact that they tend to have more positive attitudes toward information sharing than others (Table 3.2). Moreover, V-A fishers exhibit a higher level of linking ties than K-A fishers, who on average are significantly older, have more experience, and have been living in the community longer (Tables 3.2 & 3.3). Though we are unable to confirm this due to the cross-sectional nature of our data, the structure of fisher’s information sharing networks may also change over time, perhaps becoming sparser but characterized by stronger ties as individuals become more experienced. However, our situation is unique in that we are contrasting differences in social and human capital in two ethnic groups that encompass values and behavioral patterns that have interacted with very different internal and external pressures over time (Gordon 1964). Nevertheless, assessing whether increases in human capital might result in decreases in network measures of social capital among individuals in resource extraction settings would make for an interesting longitudinal study.

3.4.3 Importance of Other Stakeholder Attributes

In addition to ethnicity, we found that having a higher level of education and experience and living in the community longer were also significantly related to several measures of social capital (Table 3.3). Fishers with higher levels of education and that have lived in the community longer tend to nominate more contacts (outdegree centrality), link otherwise unconnected actors (betweenness centrality), and have more ties that bridge ethnic groups than others (bridging factor). Those with higher levels of education and experience also tend to be sought out for information and advice (indegree centrality), while more experienced fishers also link others that would be otherwise unconnected (betweenness centrality). To some extent these results are comparable to those found by Ramirez-Sanchez (2011b) among Mexican small-scale fishers
and Mailo and Johnson (1998) among commercial fishers in the southeast U.S. Specifically, Mailo and Johnson (1998) found years living in the community to be significantly related to degree centrality for commercial mackerel fishers across several Gulf states, in addition to the number of periodicals read and organizational affiliations, though years of fishing experience wasn’t examined. Among small-scale fishers in Mexico, Ramirez-Sanchez (2011b) found both experience and years in the community to be related to degree centrality; though because results varied across communities and when scaling up to include all communities, it was cautioned that they may not always be reliable predictors. In addition to education, experience is a commonly used proxy for human capital. To the extent that years living in the community reflects knowledge and skills built up over time, taken together our results add further support to the well-established relationship between human and social capital (Coleman 1988). In addition to these human capital attributes, individuals with positive information sharing attitudes also had significantly higher outdegree and betweenness centrality, suggesting they are able to spread awareness of their views to many others, some of whom are not directly connected.

Diverging from previous research on measures of network centrality in SESs (Mailo and Johnson 1998, Crona and Bodin 2006, Bodin and Crona 2008, Prell et al. 2009, Crona and Bodin 2010, Bodin and Crona 2011, Prell et al. 2011, García-Amado et al. 2012), and some of the more general social capital literature (e.g., Onyx and Bullen 2000), we found that activity in organizations was not substantially related to the tested measures of social capital, while title or role also had a negligible effect (Table 3.3). These results are interesting since these two factors have arguably been the most consistent stakeholder attributes found to be correlated with network measures of social capital. In the present study, recall that owners/industry leaders represent owners of fishing supply stores or fishing organization representatives, while the base category used for organization activity reflects individuals that have served as a board member.

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9 Mailo and Johnson (1998) applied a step-wise regression in this analysis, and among recreational mackerel fishers they did test years of experience and found it to be an important predictor, along with percent income from king mackerel and age. They also examined simple correlations between indegree centrality and organizational affiliations and measures of income among commercial shrimp fishers, where they found organizational affiliation and indegree centrality to have a significant relationship.

10 The title or role of an individual in previous studies is somewhat broadly interpreted here. For example, in the research on Kenyan fishers, fishers occupation (referred to here as title) was distinguished by their gear type (Crona and Bodin 2006, Bodin and Crona 2008, Crona and Bodin 2010, Bodin and Crona 2011); in the UK Peak District National Park study (Prell et al. 2008, Prell et al. 2009, Prell et al. 2011) roles were distinguished by stakeholder categories (e.g., agriculturist vs. conservationist); and in the study from a Mexican forest community, roles were distinguished by land ownership (Garcia-Amado et al. 2012).
or officer in local fishing organizations. Taken together, these two groups of individuals represent formal and informal leaders in the fishery that inherently possess diverse and specialized knowledge, so it is curious they do not appear to be sought out for information and advice or occupy brokerage positions more so than others. This is a critical finding for Hawaii’s fishery managers and other stakeholders, and will be discussed more in detail in the Implications for Management section.

Taken together, our results offer insight into several attributes that appear to be emerging as important predictors of individual network measures of social capital in SESs; i.e., education, years living in community, experience, and attitude toward sociability/information seeking; and highlight the crucial role of ethnic diversity in this context. Some of our findings deviated from previous research, yet studies that systematically examine the relationship between stakeholder attributes and network measures of social capital in natural resource settings are scarce, and we believe this difference is likely due to the nature of our data and statistical approach. Here, we benefited from having a complete network with a near-perfect response rate and were provided an opportunity to test multiple stakeholder attributes simultaneously in order to control for potentially competing effects, which to our knowledge is unique among existing studies. Still, we acknowledge that to some extent our results may be context specific. Moreover, social capital, more broadly defined, is a complex, multidimensional concept, and is therefore likely to have other antecedents that were outside the scope of this study.

3.4.4 Implications for Management

We see two ways that our results can inform management. First, natural resource management is increasingly moving toward assessing triple bottom line outcomes that include ecological, economic, and social outcomes (Halpern et al. 2013), and we believe the inequities in social capital across ethnic groups found here is likely to have substantial implications that speak to both economic sustainability and social equity. In terms of social equity, our results highlight social capital imbalances which are likely contributing to the marginalization and a lack of capacity to adapt to increasing regulation among at least one minority ethnic group (i.e., K-A fishers). As U.S fishery management emphasizes stakeholder participation (NOAA 2006), steps that show real progress toward ensuring K-A fishers and their concerns are adequately represented in HLF decision-making should be taken. Moreover, there needs to be a real effort
to build linking ties to the K-A community to ensure K-A fishers are provided access to technological innovations and scientific information. Our results coupled with previous research (Bodin and Crona 2011) suggests these inequities are also likely to be present in other natural resource systems with diverse stakeholders, and could be contributing to the empowerment of one group at the expense of another. Additional research into issues of racial and ethnic diversity in environmental systems would further our understanding of how inequities in social capital may be influencing access to natural capital or driving system-level outcomes through the management and policy process.

In terms of economic outcomes, social capital, as defined here, is an important factor influencing access to information and resources, and the measures we tested have all been empirically linked to economic performance (broadly defined) across a range of settings; e.g., among fishers (Mueller et al. 2008, Turner et al. 2014), farmers (Fafchamps and Minten 2002, Monge et al. 2008), students (Mihaly 2009), firms (Greve et al. 2010, Larcker et al. 2010), and scholars (Abbasi et al. 2011). Though there have been several economic studies on the HLF, including some specifically looking at vessel productivity (Sharma and Leung 1999), ethnic affiliation among actors has not been previously considered as a potential explanatory variable, nor has social capital. Yet our results in conjunction with previous work (Allen and Gough 2006, Barnes-Mauthe et al. 2013, Allen et al. 2014) suggest there may be economic disparities across ethnic groups, which can be augmented by fisheries policies and impact long-term economic sustainability. To better understand these linkages, future research should seek to explicitly examine potential differences in productivity (i.e., catch, revenue, etc.) between ethnic groups and the explicit role of social capital in this context. Though recent research in fisheries links measures of network prominence (i.e., degree centrality) to fishing success (Mueller et al. 2008, Turner et al. 2014), to our knowledge the contribution of strong ties or opportunities for brokerage have not been previously examined, though they have been shown to be important for productivity among farmers (Fafchamps and Minten 2002). Expanding this work to examine additional network measures of social capital in addition to their antecedents would help further illuminate the relationship between stakeholder diversity, social capital, and economic outcomes in SESs, and inform equitable governance that is both ecologically and economically sustainable.

The second manner in which our results can inform management is in identifying key individuals and pathways for information flow. Here, we found that identifiable industry leaders and fisher
representatives were generally not better connected than other fishers. This is a critical finding because these individuals represent the formal, and often only, pathway used by resource managers and scientists to disseminate information to resource users, yet our results suggest they are not the best conduits. Demonstrating the importance of these results, they likely help explain why there has been limited adoption of a conservation tool created by fishery scientists to help HLF fishers avoid sea turtle interactions (Howell et al. 2008), and thus fishery closures. To introduce the tool, fishery representatives were used as injection points. Yet data from subsequent focus groups indicated that the majority of fishers were not familiar with the tool and had never used it (Allen et al. 2014). The fact that a similar finding regarding the (un)connectedness of formal leaders was uncovered by Bodin and Crona (2008) among Kenyan fishers exemplifies the importance of these results for natural resource management more broadly.

Armed with our findings coupled with the previous research on central individuals in social networks that we summarized here, in the future fishery managers, scientists, and other interested parties may be able to select individuals that are more likely to be effective channels for the dissemination of information. In the case of the HLF, individuals with higher levels of education and who have lived in the community longer were found to have social capital advantages in terms of being connected to many others and bridging ethnic groups (Table 3.3), indicating they have potential for disseminating information, influencing opinions and beliefs of others, and initiating change across the fishery as a whole. Similarly, those with greater levels of experience and positive attitudes toward information sharing, which indicates a propensity to cooperate, also have social capital advantages in terms of being sought out by others, having the capacity to spread awareness of their views, and bridging otherwise unconnected actors (Table 3.3). Considering their ability to reach many others as well as different sub-groups of fishers crossing ethnic lines, individuals with a combination of these traits are likely to be ideal collaborative partners to bring into the management and policy process. They may also be the best candidates for influencing cooperation among stakeholders when ambitious and transformative changes are sought, rather than formal industry leaders. In situations where substantial and potentially controversial change is desired or necessary, for example to increase system sustainability or to initiate an institutional transformation, formal leaders are known to sometimes act as a barrier to their implementation due to having a vested interest in the status quo (Valente 2012). By comparison, individuals who do not hold formal power but who are well...
connected and able to bridge divides are thought to be more amenable and effective change agents (Valente 2012).

3.5 Conclusion

This research helps fill a critical gap in our understanding of stakeholder diversity, social networks, and social capital in SESs, and is relevant for natural resource policy, conservation, and governance. The network measures employed here as indicators of social capital have solid theoretical foundations, yet empirical evidence examining both their effects and antecedents remains limited in the environmental literature. Future studies should seek to determine whether the stakeholder attributes identified as important here are also correlated with network measures of social capital in other SESs. Additional research is equally needed to further tease out the ways in which these different forms of social capital are relevant in terms of social and ecological outcomes through their enablement or constraint on human action.
Supplementary Material

**Indegree and Outdegree Centrality**

Degree centrality is a measure of local centrality that measures the degree of a node in a graph by summing the number of other nodes that are connected to it (Freeman 1979). In our context, this can be conceptualized as the number of ties each individual fisher has; thus the degree centrality $DC$ of fisher $k$ is given by:

$$DC_k = \sum_{i=1}^{n} a(i, k)$$

(3.1)

where $a(l, k) = 1$ if fisher $l$ and $k$ are connected, otherwise $a(l, k) = 0$. In a directed graph, where we identify the direction of the tie (either outgoing or incoming), degree centrality can be distinguished by two measures: indegree, representing the number of ties coming in to an actor; and outdegree, representing the number of ties going out from an actor.

**Betweenness Centrality**

Developed by Freeman (1979), betweenness centrality measures the number of times an actor, or node, falls on the shortest path length between other actors in the network. For example, assume actor $I$ and actor $j$ are not directly connected, let $g_{ij}$ equal the number of geodesic paths present in the network from actor $I$ to actor $j$, and let $g_{ijk}$ be the number of these geodesics that pass through actor $k$. The betweenness centrality $CB$ of actor $k$ is then given by:

$$CB_k = \sum_i \sum_{j \neq i \neq k} \frac{g_{ijk}}{g_{ij}}$$

(3.2)

As such, betweenness sums the number of geodesic paths that pass through actor $k$, and then divides it by the total number of geodesics paths between actor $i$ and actor $j$. Essentially this measure gives us $k$’s portion of all paths between pairs that have to pass through or utilize actor $k$ in order to connect (Borgatti 2005).

**Efficiency**

Following Burt’s (1995) definition, the efficiency of actor $k$ is equal to the ratio of the total number of disjoint groups of primary actors who are connected to actor $k$ where the actors in
those groups are only connected to others in the same group but not to any other group, and the
number of primary actors connected to actor $k$ (which also equals the degree centrality of $k$).
Thus, efficiency for fisher $k$ is given by:

$$E_k = \frac{g_k}{DC_k}$$

(3.3)

where $g_k$ denotes the number of disjoint groups of primary contacts of fisher $k$ and $DC_k$
represents the degree centrality of fisher $k$. 


References


Ramirez-Sanchez, S. 2011a. The role of individual attributes in the practice of information sharing among fishers from Loreto, BCS, Mexico. Pages 234-254 in Ö. Bodin and C.


Chapter 4

SOCIAL NETWORKS AND ENVIRONMENTAL OUTCOMES: HOMOPHILY AND RATES OF INCIDENTAL CATCH

Abstract

Social networks can profoundly affect human behavior – the primary force driving change in environmental systems. Until recently, however, data has not been available to link social networks to human behaviors directly impacting ecosystems. We examine network-level effects of homophily – the tendency for actors to associate with similar others – on rates of shark bycatch, a global environmental issue. We find that ethnic homophily is strongly related to shark bycatch, and that actors whose majority ties fall outside their ethnic group behave more like their network group, rather than their ethnic group. Our results provide novel empirical evidence that network homophily may impede the diffusion of sustainable behaviors – behaviors that might have mitigated the unwanted catch of over 46,000 sharks from 2008 – 2012 in a single fishery.

4.1 Introduction

Human behavior represents the primary force driving change in environmental systems (Axelrod 1994, Bodin and Prell 2011). Human behavior is also profoundly affected by social interactions (Christakis and Fowler 2007, 2008, Centola 2011). As the global human population continues to expand and challenge the ecological balance on which our survival depends (Axelrod 1994), it is critical to understand how social interactions scale up to influence environmental outcomes (Bodin and Prell 2011).

Social networks serve as primary channels for the flow of information and resources which can provide people with opportunities and facilitate human action (Burt 1992, Rogers Everett 1995). Social interactions with our friends, family, and neighbors can directly affect our beliefs,

11 This chapter is formatted for submission to the journal Science. Section headings have been added, and figure and table numbers were adjusted to align with the organization of this thesis. At present, the full citation is: Barnes, M., Lynham, J., Kalberg, K., and P.S. Leung. 2015. Social Networks and Environmental Outcomes. Working paper.
decisions, and behaviors (Christakis and Fowler 2007, 2008). Beyond simply the existence of ties between individuals, the degree to which information and behaviors spread through social networks is greatly affected by its topological structure (Blau and Schwartz 1984, Rogers Everett 1995, Watts 1999, Centola 2010).

One of the most basic factors governing social network structure is the concept of homophily – the tendency for actors to associate with others who are similar to themselves (Lazarsfeld and Merton 1954, Marsden 1987, McPherson et al. 2001). Homophily can heavily influence the structure of social networks and their effects on people’s lives. As people seek out similar others, social networks become highly clustered (Marsden 1987, Moody 2001, Barnes-Mauthe et al. 2013). Clustered social networks driven by homophily can create “fault lines” in patterns of interactions among people that inhibit communication, learning, and the diffusion of innovations across groups (Rogers Everett 1995, Centola 2010, Golub and Jackson 2012). Recent theoretical work suggests diffusion across such divisions is particularly unlikely in the case of complex contagions (Centola and Macy 2007).

Conversely, a long history of research on social interaction shows people are more likely to be influenced by others who are similar to themselves (Rogers Everett 1995, McPherson et al. 2001). Likewise, the more tightly individuals are bound in a network, the more they are pressured by uniformity and affected by groups standards (Friedkin 1984).

This homophily thesis has important implications for human behavior. As networks become segregated along some trait or set of traits, knowledge, attitudes, and beliefs can become homogenous and localized, and differences across groups exacerbated (McPherson et al. 2001). If homophily indeed leads to clustered social networks where social influence is enhanced within groups (McPherson et al. 2001), while the diffusion of information and innovations across groups is inhibited (Golub and Jackson 2012), we would expect to observe different behaviors across groups stemming from segregated social networks. Yet, with a few notable exceptions (Aral et al. 2009, Centola 2011), much of what we know about homophily in social networks derives from the theoretical literature (Axelrod 1997, Currarini et al. 2009, Golub and Jackson 2012). Whether significant differences in behaviors exist across groups in highly segregated social networks driven by homophily therefore remains an important empirical question.
The effects of homophily-driven network segregation may be particularly important in the context of environmental systems. Environmental systems are often characterized by diverse groups of actors competing over limited common-pool resources (CPRs) – actors whose decision-making and behaviors can have direct impacts on ecosystems (Ostrom et al. 1994). This environment of heightened competition is critical because it can cause differences across groups to be emphasized (Baerveldt et al. 2004). In environmental systems, homophily-driven network segregation is thus likely to prevent the diffusion and adoption of particular behaviors across network fault lines, leading to inefficiencies and potentially undesirable environmental outcomes.

As policy-makers and resource managers struggle to devise effective strategies to sustain both natural and human capital in the face of growing human impacts on the natural environment, recent research has emphasized that understanding the relationship between social interactions and success and failures in resource governance is critical (Bodin and Prell 2011). Yet research quantitatively linking social networks to human behavior in environmental systems has been limited to only a handful of studies limited by a lack of data on complete networks, observed behaviors, and appropriate controls (e.g., Mueller et al. 2008, Conley and Udry 2010). Here, we work toward filling this critical knowledge gap by examining network-level effects of homophily on rates of shark bycatch among large-scale commercial tuna fishers as an example of an environmental outcome.

4.1.1 Fisheries Bycatch: an Environmental and Economic Problem

Fisheries bycatch – the incidental catch of non-target species – is a significant global environmental issue with a range of ecological, economic, and social impacts. High rates of bycatch can have dramatic effects on marine ecosystems by causing population declines, removing top predators, and altering foraging behaviors of proximate species (Lewison et al. 2004). Concern over bycatch is also one of the most common causes of increased regulation in fisheries, which can have cascading economic impacts on fishers and fishing communities (Gilman et al. 2008). In addition, bycatch is often discarded, calling into question the ethical issues of waste (Gilman et al. 2008). Shark bycatch, which we examine here, has been cited as a primary threat to declining shark populations worldwide (Lewison et al. 2004).

4.2 Methods
Though shark bycatch rates typically exhibit a high level of variability related to spatiotemporal factors, they can also be driven by fishing behaviors (Bromhead et al. 2012). To investigate how fishing behaviors related to shark bycatch are potentially driven by network homophily, we leveraged a complete information sharing social network dataset on the population of fishers operating in Hawaii’s Longline Fishery (HLF), where sharks are caught in large numbers and comprise the majority of all bycatch. We linked this data to longitudinal data on catch and effort collected by NOAA’s Pacific Islands Regional Office (PIRO) Observer Program over a period of five years to examine the relationship between network-level homophily and rates of shark bycatch.

A critical assumption made is that fisher’s social networks provide a means by which fishers can obtain information that can aid them in employing effective bycatch avoidance strategies. These strategies may include, but are not limited to, adopting different gear technologies or fishing behaviors, such as cooperating to actively avoid bycatch hotspots while at sea. In line with the literature on homophily, diffusion, and network subgroups (Friedkin 1984, Rogers Everett 1995, McPherson et al. 2001), we expect that actual adoption of particular strategies is more likely to occur within network subgroups driven by preferences for within group ties (homophily), and may not cross over critical network fault lines (Centola and Macy 2007, Golub and Jackson 2012), potentially resulting in divergent fishing behaviors that can directly impact shark bycatch, and thereby ecosystem sustainability.

Described in greater detail in Chapter 2, HLF is a limited-entry, multimillion-dollar industry supplying domestic and international markets with fresh tuna and swordfish, and is the largest commercial fishing sector in the Hawaiian Islands. From 2008 to 2012, there were 122 to 129 active vessels that completed between 1,205 – 1,381 annual fishing trips generating revenues of $65 - $94 million USD per year. The fishery is comprised of three distinct ethnic groups: Vietnamese-Americans (V-A), European-Americans (E-A) and Korean-Americans (K-A), all of which target tuna (primarily bigeye, *Thunnus obesus*) for at least a portion of the year (Barnes-Mauthe et al. 2013). Though a handful of V-A vessels also target swordfish, they are closely tied via social affiliations and there is little variation in their fishing behaviors. We therefore focus solely on tuna trips in this analysis, in which all fishers participate. 20% of all Hawaii-based longline tuna trips are federally mandated to carry an onboard fisheries observer that collects detailed data on catch and effort for every fishing set. The observer data over the five-year period included a total sample of 18,059 fishing sets, of which 5,997 were missing key variables.
This resulted in a usable sample of 12,062 fishing sets from 867 observed trips made by 120 unique individual fishers (Table S4.1). In the sample, a typical tuna trip lasted anywhere from two and a half to four weeks, and was comprised of approximately 14 ± 4 (μ ± σ) fishing sets containing 2,327 ± 409 hooks each (Table S4.2). Across all sets in the sample, the mean rate of shark bycatch was 4.603 ± 5.331 per fishing set (Table S4.1).

Described in greater detail in Chapter 2, the information sharing network data is cross-sectional and was collected from primary decision-makers associated with active vessels in Hawaii's longline fleet from May 2011 – January 2012 (Barnes-Mauthe et al. 2013). Primary decision-makers are defined as vessel owners and captains, which we refer to collectively as ‘fishers.’ Fishers were specifically asked to nominate up to ten individuals with whom they commonly shared important fishery-related information. Fishers were also asked to report how often they shared information with each contact, how valuable they felt the information was, and the degree to which their personal information-sharing network may have changed over the past five years. A high response rate was achieved, including 90% of all fishers tied to 93% of all active vessels during the time of data collection (see Chapter 2 and the Supplementary Material included with this chapter for further information on data collection and the sample).

Fishing can be characterized as a competitive economic pursuit – particularly in this fishery which, unlike many other U.S. commercial fisheries, has not been rationalized by the implementation of a rights-based management scheme (Costello et al. 2008). In this context, information that may aide fishers in increasing their fishing efficiency (and therefore mitigating bycatch) is not likely to be shared indiscriminately. We therefore dropped all ties identified as “not valuable” for information sharing, in addition to all ties that were used less frequently than one to three times per month. We also dropped all nodes that stated their network had completely changed over the last five years to account for the cross-sectional nature of the network data. The resulting network included 179 nodes (159 of which are fishers), 857 ties, 138 reciprocal ties, a mean geodesic distance of 4.42, an average degree of 8.246 network neighbors, and three components: one weakly connected component containing all but two nodes, and two isolates.

The network exhibits strong homophily (see Supplementary Material), with the majority of fishers organizing themselves into three distinct ‘network groups’ largely corresponding to ethnicity (see Fig. 4.1). Out of the 159 fishers present in the network, only six have a majority of ties outside
their ethnic group, while one has an equal proportion of intra and inter-ethnic group ties. We refer to these individuals as outliers. Excluding these outliers, we tested the effect of these network groups driven by ethnic homophily on rates of shark bycatch across our sample of observed tuna fishing sets from 2008 – 2012. Due to the count nature of shark interactions and the prevalence of overdispersion, we employed a negative binomial regression model with standard errors clustered to account for multiple observations of 120 unique individual fishers. We also accounted for spatiotemporal factors known to effect shark bycatch (see Supplementary Material).

**Figure 4.1 Bycatch by Network Group.** A depiction of HLF information sharing network, generated in NetDraw (Borgatti 2002) using the spring embedding algorithm. Each node corresponds to an individual fisher colored coded by ethnicity, or an actor deemed important for information sharing by respondents (i.e., industry leader, government or management official). Circled nodes with solid lines denote fishers who have a majority of ties outside their ethnic group, with the color of the circle corresponding to the group they have a majority of ties to. Circled nodes with gray dashed lines denote nodes with an equal proportion of ties both within and outside their ethnic group. Excluding these outliers, mean ($\mu$) shark bycatch per 1,000 hooks and standard deviations ($\sigma$) are reported by group.
4.3 Results and Post-Hoc Analysis

Our results show a statistically significant difference in shark bycatch between the E-A network compared to both the V-A and K-A network (Table 4.1, Table S4.4), suggesting homophily-driven network segregation is related to differences in fishing behaviors affecting rates of shark bycatch. Clearly distinguishing this as a network effect rather than a cultural effect is, however, somewhat problematic. In this case, the primary factor driving homophily is ethnicity (see Supplementary Material and Barnes-Mauthe et al. 2013), which may be correlated with cultural differences independent of network interactions that influence fishing behaviors, e.g., cultural norms. Yet the close association of homophilous network structures with ethnicity problematizes including ethnicity as a potential control in our original model. However, if ethnicity-dependent cultural norms are in fact driving the differences in fishing behaviors we have captured here, we would expect those whose majority of ties fall outside their ethnic group (outliers) to be acting more like their ethnic group, rather than their network group, where their network group is defined as the group they have a majority of ties to.

Table 4.1 Network homophily effects on bycatch. Values shown are coefficients from two negative binomial regressions. The dependent variable is shark per fishing set in Hawaii’s deep-set tuna longline fishery from 2008 - 2012 (n = 12,062). Controls include target species catch, vessel length, number of hooks, set location, soak time, temperature, type of bait, seasonality, lunar variability, and annual variability. Standard errors are clustered to account for multiple observations of 120 individual fishers.

<table>
<thead>
<tr>
<th>Network group</th>
<th>Regression 1</th>
<th>Regression 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>E-A network</td>
<td>-0.217 (0.049)*</td>
<td>(base)</td>
</tr>
<tr>
<td>K-A network</td>
<td>-0.031 (0.052)</td>
<td>0.187 (0.053)*</td>
</tr>
<tr>
<td>V-A network</td>
<td>(base)</td>
<td>0.217 (0.049)*</td>
</tr>
</tbody>
</table>

* indicates significance at < 0.05.

To test for this effect, we examined whether observed outliers’ rates of shark bycatch were significantly different than their ethnic or network group. Of the seven outliers, the observer data included observations of four (Table S4.2). Three of these outliers had a majority of ties outside their ethnic group, two of which are of particular interest because they spanned network groups that were found to have significantly different rates of shark bycatch (outliers #57 and #59, who spanned the K-A and E-A networks). Interestingly, results from negative binomial regressions
show these two outliers had significantly different rates of shark bycatch than their ethnic group, yet their rates were not significantly different than their network group, defined as the group they have a majority of ties to (Table 4.2, S4.5). In short, they appear to be acting much more like their network group, rather than their ethnic group.

Table 4.2 Are Outliers Acting More Like their Ethnic Group, or their Network Group? Values shown are coefficients from four negative binomial regressions (A - D). The dependent variable is shark per fishing set in Hawaii’s deep-set tuna longline fishery from 2008 – 2012 (n = 12,062). Network variables account for observed homophilous groupings along ethnic lines; outliers designate circled nodes in Fig. 4.1, which are independently tested to determine if their rates of shark bycatch are significantly different than their ethnic or network group. Controls include target species catch, vessel length, number of hooks, set location, soak time, temperature, type of bait, seasonality, lunar variability, and annual variability. Standard errors are clustered to account for multiple observations of 120 individual fishers. In each model (A – D), the network groups in question are bold, and the group aligned with the ethnic background of the outlier is delimited with the colors corresponding to Fig 4.1.

<table>
<thead>
<tr>
<th>A. Regression with outlier #57 as the base, who is E-A with a majority of ties to the K-A network</th>
<th>B. Regression with outlier #59 as the base, who is K-A with a majority of ties to the E-A network</th>
</tr>
</thead>
<tbody>
<tr>
<td>E-A network</td>
<td>-0.171 (0.030)*</td>
</tr>
<tr>
<td>K-A network</td>
<td>0.017 (0.055)</td>
</tr>
<tr>
<td>V-A network</td>
<td>-0.047 (0.044)</td>
</tr>
<tr>
<td>C. Regression with outlier #81 as the base, who is K-A and has ties split between the K-A network, the V-A network, and other non-fishers</td>
<td>D. Regression with outlier #97 as the base, who is K-A and has a majority of ties to the V-A network</td>
</tr>
<tr>
<td>E-A network</td>
<td>-0.144 (0.067)*</td>
</tr>
<tr>
<td>K-A network</td>
<td>0.045 (0.057)</td>
</tr>
<tr>
<td>V-A network</td>
<td>0.073 (0.042)</td>
</tr>
</tbody>
</table>

* indicates significance at < 0.05.

Though the two remaining outliers (outlier #97 and #81) did not span network groups with significantly different rates of shark bycatch, their individual rates of shark bycatch are also in line with our hypothesis. One (#97) spanned network groups found to have similar rates of shark bycatch (the K-A and V-A networks), and their rate was not significantly different than their ethnic or network group (the K-A and V-A networks, respectively), yet was significantly different than the remaining group they were not directly affiliated with (the E-A network, see Table 4.1, S4.4). The remaining outlier (#81) had an equal proportion of intra- and inter-ethnic group relations, and their rate of shark bycatch was also not significantly different from their ethnic group or the other ethnic-network group they affiliated with (the K-A and V-A networks,
respectively). It was, however, significantly different from the group they were not directly tied to (the E-A network, Table 4.2, S4.5).

Though our analysis of outliers is inherently limited by the small number of them present in our network, our results lend support for a network effect, rather than a cultural effect, being captured in our original model (Table 4.1). In other words, our results support the hypothesis that social affiliations are indeed tied to fishing behaviors that can scale up to have a direct impact on ecosystems.

4.4 Discussion and Conclusion

Here, we offer novel empirical evidence that social affiliations are tied to environmental behavior, and that homophily-driven network segregation may impede the diffusion of sustainable behaviors. The magnitude of this impact is worthy of both scholarly and policy attention. Notably, a coarse ad-hoc analysis suggests that if all fishers had the same shark bycatch rate as the most efficient network group with the lowest rate (the E-A network, 1.776 sharks per 1,000 hooks; Table S4.2), interactions with approximately 4,154 sharks observed in our sample might have been avoided. Applying this same rate to all hooks reported in federal logbooks across all tuna fishing trips from 2008 – 2012, and comparing it to the mean shark bycatch for all fishers observed in our sample (1.996 sharks per 1,000 hooks; Table S4.2), we estimate that from 2008 - 2012, interactions with ~ 46,339 sharks might have been avoided, representing an estimated 12% reduction in overall shark bycatch in HLF.

Our approach also suffers some limitations. First, due to the cross-sectional nature of our data, the casual direction between network homophily and environmental behaviors is difficult to statistically establish. Do fishers organize themselves into social groups based on bycatch behaviors, or are bycatch behaviors influenced by social groups? Given the number of controls in our model and the fact that bycatch is a byproduct of the pursuit of an economic activity (tuna fishing), we believe the former is rather unlikely. However, firmly establishing the causal mechanisms underlying the observed correspondence between homophily-driven network structure and behaviors effecting environmental outcomes will require dynamic network data collected at multiple points in time.
As is the case with many scientific inquiries, our results also seem to uncover more questions than answers. Namely, what, exactly, is the more efficient group of fishers (the E-A network) doing differently that has enabled them to mitigate shark bycatch more effectively than others? Are they cooperating at sea by sharing information about fishing locations in order to avoid bycatch hotspots? Have they adopted innovative technologies that facilitate more efficient fishing practices, thereby enabling them to better mitigate shark bycatch? Though available data allowed us to control for fishing location, our model does not capture the dynamic behavior of fishers in time and space that would help to shed light on explicit cooperation at sea. Similarly, we did not have detailed information on all technology each vessel was equipped with. Obtaining clear answers to these questions will be critical for informing effective policy, and they certainly warrant future research.

Despite the limitations of our data and empirical approach, our results offer novel empirical evidence that patterns of social structure driven by a propensity for individuals to interact with similar others correlates with behaviors that can directly impact ecological sustainability. In this case, the bottom line is that some fishers embedded in cooperative networks of information sharing exhibit more sustainable fishing behaviors that better mitigate shark bycatch, yet fault lines in the network appear to prevent these behaviors from being adopted by all fishers. In other words, social affiliations appear to be tied to fishing behaviors that can scale up to have a direct impact on ecosystems.
Supplementary Material

S4.1 Study System

In HLF, fishing sets consisting of a single mainline hanging thousands of individually hooked lines are stretched over vast portions of the water column. A map depicting the range of Hawaii’s longline fleet can be found in Fig. 2.1, Chapter 2. Fishers typically lay one set per day, letting the hooks soak an average of five hours before haul out. Sets are intended to catch either swordfish or tuna, yet several other species are also incidentally caught. This incidental catch is referred to here as bycatch – a common term for the incidental take of non-target or protected, endangered, or threatened species. Sometimes bycatch can be marketed, but in many cases it is deemed unusable or otherwise unwanted due to regulatory restrictions or a lack of marketability and is discarded at sea, either alive and injured, or dead.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Days/trip</td>
<td>22.578</td>
<td>5.174</td>
</tr>
<tr>
<td>Sets/trip</td>
<td>13.912</td>
<td>3.554</td>
</tr>
<tr>
<td>Bigeye tuna/set</td>
<td>9.106</td>
<td>9.388</td>
</tr>
<tr>
<td>Shark/set</td>
<td>4.063</td>
<td>5.331</td>
</tr>
<tr>
<td>Bigeye tuna per 1,000 hooks</td>
<td>3.925</td>
<td>4.116</td>
</tr>
<tr>
<td>Shark per 1,000 hooks</td>
<td>1.996</td>
<td>2.322</td>
</tr>
</tbody>
</table>

In HLF, where sharks comprise a substantial portion of total incidental catch (Walsh et al. 2009), fishers have incentives to avoid shark bycatch. Sharks hold little to no economic value due to a lack of market for shark meat in Hawaii (Gilman et al. 2008), and though in some fisheries shark fins are retained due to their high export value, there are strict bans on shark finning in Hawaii, i.e., a federal and Hawaii state ban on shark finning has been in place in since 2000, effectively prohibiting shark finning in most cases unless the carcass is retained (which takes up premium space that fishers could otherwise be using for high value tuna). In 2010, an additional ban on the possession, distribution, and sale of shark fins was enacted throughout the state of Hawaii. Additionally, interactions with sharks can lead to the loss of target species due to shark
predation, potential damage or loss of gear, risk of injury to the captain or crew, and an expenditure of time removing sharks from gear (Gilman et al. 2008).

S4.2 Data construction

S4.2.1 Network Data

The network data employed in this analysis was originally collected by Barnes-Mauthe et al. (2013) from May 2011 – January 2012, and is described in detail in Chapter 2. In this analysis, we included all information sharing ties identified by the 143 respondents, resulting in a network of 179 nodes, 159 of which were fishers (Fig. 4.1).

S4.2.2 Fisheries Observer Data

Detailed data on catch and effort on 20% of all Hawaii-based deep-set tuna longline trips is collected by the National Oceanic and Atmospheric Administration (NOAA)’s Pacific Islands Regional Office onboard observer program. We were granted access to observer data from 2008 – 2012. The data included detailed information on 18,059 sets from a reported total of 85,989 (according to federal logbooks) laid by Hawaii-based tuna longline fishers during the five-year period, thus equating to 21% of all sets.

When onboard, observers monitor interactions with protected species while recording an array of operational details for every fishing set. The data thus included a host of controls that can be used to model shark bycatch. In longline fisheries, shark bycatch is typically modeled as catch per unit effort (CPUE), defined as sharks caught per fishing set or per 1,000 hooks. We used sharks caught per set as our outcome variable. For reference, the most commonly caught species of shark in the deep set tuna longline fishery is blue shark (Prionace glauca), followed by bigeye thresher (Alopias superciliosus), shortfin mako (Isurus oxyrinchus), oceanic whitetip (Carcharhinus longimanus), silky shark (C. falciformis), and crocodile shark (Pseudocarcharias kamoharai) (Walsh et al. 2009). Other species are sometimes also caught, but at rates of less than 1% of total shark bycatch.

A handful of studies have found shark bycatch rates in longline fisheries to be influenced by (1) spatio-temporal variables, i.e., latitude, longitude, and seasonality (2) environmental variables, such as sea surface temperature and moon phase, and (3) operational characteristics, such as
vessel size, bait type, fishing pressure (Walsh et al. 2009, Bromhead et al. 2012). The observer data included information on latitude, longitude, sea surface temperature, vessel size, and bait type for every set. Latitude, longitude, and temperature were recorded at both the beginning and end of each set. We used the location at the beginning and took the average temperature for each set. The observer data also included variables that we used as proxies for effort, i.e., soak time (time the baited hooks are left to soak in the water column) and number of target species caught (i.e., bigeye tuna). To create a seasonality variable, we maximized the correlation of sine functions of sharks caught per set by adjusting the day of the year (Julian date) divided by the number of days in a year. In addition to the seasonality variable, another cyclical variable was created to represent the lunar cycle using a sine function that equals 1 during a full moon and -1 during a new moon.

We assigned unique identifiers to all individuals present in our network data set. Using a two-stage approach and taking exceptional care to protect the confidentiality of fisher’s personal identifying information, we linked fishery observer data to our data on fisher’s social networks at the individual fisher level. All identifying information was immediately removed after the data was successfully merged and checked for accuracy. Of the 18,059 observed sets, 12,421 were linked to fishers represented in our network. 150 of these observed sets were subsequently dropped due to missing key information on temperature, set location, or shark catch. We also dropped all observations tied to fishers who claimed their network had completely changed over the last five years to account for the cross-sectional nature of our network data (209 sets total), resulting in a usable sample of 12,062 fishing sets over the five-year period.

S4.3 Data description

S4.3.1 Network Data

Basic network statistics are provided in Chapter 2. Of particular significance here is that the network exhibits strong homophily along ethnic lines, with a statistically significant E-I homophily index of -0.764 (where -1 indicates extreme homophily and +1 indicates extreme heterophily; p < 0.05). A previous analysis explored the role of additional individual-level attributes on homophily in this network (such as title, education, age, and experience) using a density model
of variable homophily, and found that ethnicity was the primary source of homophily (Barnes-Mauthe et al. 2013).

S4.3.2 Fisheries Observer Data

Figures S4.1 to S4.3 and Tables S4.1 to S4.3 contain information on fishery participation, tuna fishing trips, shark bycatch, and spatiotemporal and operational covariates. Fishery participation remained relatively stable from 2005 to 2012, averaging at 127 permitted vessels completing an average of 1300 trips per year (Fig S4.1) spanning a wide geographic range (Fig. 2.1). Trips lasted a mean of 23 days and were comprised of an average of 14 sets and 2,327 hooks each (Table S4.1 & S4.2). Shark bycatch across all fishers averaged at $4.603 \pm 5.331$ per set and $1.996 \pm 2.322$ per 1,000 hooks over the five year period, though rates varied to some degree between ethnic and network groups (Table S4.2, Fig. S4.3). Bigeye tuna catch (the target species) averaged at $9.106 \pm 9.388$ per set and $3.925 \pm 4.116$ per 1,000 hooks (Table S4.1, Fig. S4.2). Presented in Table S4.3, the average vessel length was $71.224 \pm 9.949$ feet. The latitude and longitude where sets begun averaged at 22.196 and -157.462, respectively. Sets were soaked for a mean of 4.697 hours in an average sea surface temperature of 77.032 Fahrenheit. Sanma was the most commonly used bait type, though some fishers also used sardines and a mix of different types of bait.

![Figure S4.1 Total Active Vessels and Trips Per Year, 2008 – 2012.](image-url)
Figure S4.2 Declared Tuna Trips CPUE. Total bigeye tuna and shark caught per 1000 deep-set hooks, 2008 – 2012.

Figure S4.3 Distribution of Shark Per Fishing Set.
Table S4.2 Descriptive Statistics, Shark Bycatch.

<table>
<thead>
<tr>
<th></th>
<th>Total fishers</th>
<th>Fishers observed&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Observed trips</th>
<th>Observed sets (N)</th>
<th>Shark per set</th>
<th>Shark/1,000 hooks</th>
<th>No. hooks/set</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
</tr>
<tr>
<td>All fishers</td>
<td>145</td>
<td>120</td>
<td>867</td>
<td>12,062</td>
<td>4.603</td>
<td>5.331</td>
<td>1.996</td>
</tr>
<tr>
<td>E-A fishers</td>
<td>52</td>
<td>46</td>
<td>371</td>
<td>4793</td>
<td>4.386</td>
<td>4.982</td>
<td>1.776</td>
</tr>
<tr>
<td>V-A fishers&lt;sup&gt;b&lt;/sup&gt;</td>
<td>70</td>
<td>51</td>
<td>297</td>
<td>4624</td>
<td>5.260</td>
<td>5.843</td>
<td>2.339</td>
</tr>
<tr>
<td>Network Groups, not including outliers</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>E-A network</td>
<td>51</td>
<td>45</td>
<td>362</td>
<td>4694</td>
<td>4.365</td>
<td>4.968</td>
<td>1.765</td>
</tr>
<tr>
<td>K-A network</td>
<td>20</td>
<td>20</td>
<td>172</td>
<td>2281</td>
<td>3.84</td>
<td>5.034</td>
<td>1.759</td>
</tr>
<tr>
<td>V-A network&lt;sup&gt;b&lt;/sup&gt;</td>
<td>69</td>
<td>51</td>
<td>297</td>
<td>4624</td>
<td>5.261</td>
<td>5.843</td>
<td>2.339</td>
</tr>
<tr>
<td>Outliers</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>#57 (E-A, majority K-A)</td>
<td>1</td>
<td>1</td>
<td>9</td>
<td>99</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<tr>
<td>#59 (K-A, majority E-A)</td>
<td>1</td>
<td>1</td>
<td>7</td>
<td>88</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>#81 (K-A, split)</td>
<td>1</td>
<td>1</td>
<td>9</td>
<td>123</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>#97 (K-A, majority V-A)</td>
<td>1</td>
<td>1</td>
<td>11</td>
<td>153</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>#63 (K-A, majority E-A)</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>#69 (V-A, majority E-A)</td>
<td>1</td>
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<td>0</td>
<td>0</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>#72 (E-A, majority V-A)</td>
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<td>0</td>
<td>0</td>
<td>0</td>
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<tr>
<td>Final Network Groups&lt;sup&gt;c&lt;/sup&gt;</td>
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<td>4694</td>
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<td>4.968</td>
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<td>K-A network</td>
<td>23</td>
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<td>V-A network</td>
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<td>51</td>
<td>297</td>
<td>4624</td>
<td>5.261</td>
<td>5.843</td>
<td>2.335</td>
</tr>
</tbody>
</table>

<sup>a</sup> Defined as fishers who captained a tuna targeting trip with a NOAA fisheries observer onboard between 2008-2012; approximately 20% of all tuna trips are observed.

<sup>b</sup> Some fishers in this group also participate in swordfish fishing; swordfish trips are not included in this analysis.

<sup>c</sup> In the final network groups 57 was included in the K-A network, 59 was included in the E-A network, and 81 and 97 remained in the K-A network, see Table 2). Note: Shaded boxes represent values that are protected by federal law due to confidentiality agreements, which protect all data pertaining to less than three aggregated individuals.
Table S4.3 Descriptive Statistics, Model Covariates.

<table>
<thead>
<tr>
<th>Variable (variable name)</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bigeye tuna/set (tuna)</td>
<td>9.106</td>
<td>9.388</td>
</tr>
<tr>
<td>Vessel Length (len)</td>
<td>71.224</td>
<td>9.949</td>
</tr>
<tr>
<td>No. hooks/set (hks)</td>
<td>2327.052</td>
<td>409.217</td>
</tr>
<tr>
<td>Latitude (°N) (lat)</td>
<td>22.196</td>
<td>5.929</td>
</tr>
<tr>
<td>Latitude2 (lat^2)</td>
<td>527.813</td>
<td>252.335</td>
</tr>
<tr>
<td>Longitude (°W) (lon)</td>
<td>-157.462</td>
<td>7.251</td>
</tr>
<tr>
<td>Longitude2 (lon^2)</td>
<td>24846.740</td>
<td>2264.203</td>
</tr>
<tr>
<td>Soak Time (soaktime)</td>
<td>4.697</td>
<td>1.416</td>
</tr>
<tr>
<td>Temperature (F) (temp)</td>
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</tr>
<tr>
<td>Temperature2 (temp^2)</td>
<td>5942.712</td>
<td>450.535</td>
</tr>
<tr>
<td>Bait (bait)</td>
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<td></td>
</tr>
<tr>
<td>Mixed (base)</td>
<td>0.107</td>
<td>0.309</td>
</tr>
<tr>
<td>Sanma</td>
<td>0.851</td>
<td>0.356</td>
</tr>
<tr>
<td>Sardine</td>
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<td>Lunar (lunar)</td>
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<td>0.414</td>
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<tr>
<td>2012</td>
<td>0.215</td>
<td>0.411</td>
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S4.4 Model Structure

Catch data for non-target species such as sharks can be characterized as count data, and therefore call for models appropriate for non-negative integer-valued random variables. Due to its flexibility in modeling count data, the Poisson regression model has been used to model rates of incidental catch of many non-target species, including shark bycatch in HLF (33). The Poisson model assumes that the response variable has a Poisson distribution, which expresses the probability of an event occurring within a fixed interval of time and/or space, and assumes its expected value can be modeled by a linear combination of unknown parameters. In the Poisson regression model the parameter $\lambda_i$, known as the rate of occurrences (which can also be characterized as the count or mean), for each case $i$ is given by:

$$
\lambda_i = \exp(X_i' \beta)
$$

(4.1)

where $\lambda$ is a function of a vector of predictor variables, and is also the expected value of any Poisson random variable of the $i$th entity at time $t$, $X_i$ is a vector of the $i$th entity’s characteristics and other explanatory variables, and $\beta$ is a conformable matrix of unknown
parameters to be estimated. The exponential functional form in (4.1) ensures a non-negative solution for all $X$ and $\beta$, and is thus particularly suited for modeling somewhat rare events, such as shark bycatch, where non-occurrences or zero-valued observations may occur at any given time. The Poisson probability specification is then:

$$\Pr(y|\lambda) = \frac{e^{-\lambda} \lambda^y}{y!}, \text{ for } y = 1, 2, 3, \ldots, \infty \tag{4.2}$$

where $y$ is the number of times an event occurs. The model assumes that the probability of an event occurs within a small interval of time, and that occurrences in different time intervals are independent events. The expected value is assumed to be proportional to some measure of scale, or exposure. In modeling incidental catch, the scale or exposure variable can be proportional to the number of fishing sets per trip, and different exposure times can be incorporated into the model as:

$$\lambda_i t_i = \exp(X_i \beta_i \epsilon_i) = \exp(X_i \beta + \ln t_i) \tag{4.3}$$

where $t_i$ is the amount of time that observation $i$ may experience an occurrence of the event in question (such as the fishing set) and $\lambda_i$ is the rate of occurrences (e.g., the expected number of observations during the set). The Poisson model can be estimated by the maximum likelihood method.

The Poisson regression model assumes that the variance of the data is equal to the conditional mean, yet overdispersion in count data is common. In the case of overdispersion, the negative binomial distribution can instead be employed, which extends the Poisson model to allow the variance to diverge from the mean. In a negative binomial distribution, the mean is re-specified as:

$$\lambda_i = \exp(X_i \beta) \exp(\epsilon_i) = \lambda_i \exp(\epsilon_i) = \lambda_i \delta_i \tag{4.4}$$

where $\exp(\epsilon_i)$ has a gamma distribution with a mean 1.0 and a variance $\alpha$, and $\epsilon$ is a random error that is assumed to be uncorrelated with $X$. The negative binomial distribution is then:
\[
P(y_i | X_i) = \frac{\Gamma(y_i + v_i)}{y_i! \Gamma(v_i)} \left( \frac{v_i}{v_i + \lambda_i} \right)^{v_i} \left( \frac{\lambda_i}{v_i + \lambda_i} \right)^{y_i}
\]  

(4.5)

where \( v_i = \alpha^{-1} \), and \( \alpha \) is the dispersion parameter such that \( \text{Var}(y_i) = E(y_i)\{1 + \alpha E(y_i)\} \), which is an additional parameter to be estimated not included in the basic Poisson model. The model can then be estimated using the maximum likelihood method.

**S4.5 Model Estimation**

To test whether network-level homophily in Hawaii’s longline fishery information sharing network was related to shark bycatch, we ran a series of negative binomial regression models including the spatiotemporal and operational characteristics presented in Table S3 as covariates. The distribution of shark bycatch displayed signs of overdispersion, with a variance over six times larger than the mean (\( \sigma^2 = 28.420, \mu = 4.603 \)), suggesting a Poisson regression would be inappropriate. A goodness of fit test from a Poisson regression on shark bycatch per fishing set including the covariates presented in Table S3 confirmed that the Poisson model was inappropriate (\( \chi^2 = 34451.96, p = 0.000 \)). We therefore fit a negative binomial regression model to shark bycatch per fishing set using the nbreg function in Stata. The empirical model is defined in Eq. 6 as:

\[
y_i = \exp(\beta_0 + \beta_t \text{tuna} + \beta_{s, \text{len}} + \beta_{s, \text{hks}} + \beta_{s, \text{lat}} + \beta_{s, \text{lon}} + \beta_{s, \text{lon}}^2 \\
+ \beta_{o, \text{temp}} + \beta_{o, \text{temp}}^2 + \beta_{o, \text{season}} + \beta_{o, \text{lunar}} \\
+ \delta_{s, \text{network}} + \delta_{s, \text{bait}} + \delta_{s, \text{year}} + \theta \text{soaktime})
\]

(4.6)

All variables aside from the one labeled ‘network,’ which refers to network groups, are defined in table S4.3. To determine network groups, the global network was qualitatively separated into three groups based on ethnicity due to the strong presence of ethnic homophily (Fig. 4.1). In defining these groups we first excluded outliers, defined as individuals whose majority of ties did not fall within their ethnic group. There were seven outliers total, four of which were present in the observer data (Table S4.2).

Described in the main text, we first tested whether there was any difference in mean shark bycatch among the three network groups. We then tested whether outliers behaved more
similarly to their network or ethnic group, where their network group was defined as the group they had a majority of ties to. Full models results are presented in Tables S4.4 and S5.5.

### Table S4.4 Global Network Homophily Effect on Shark Bycatch.

Negative binomial regression outcome of shark bycatch in HLF. The dependent variable is shark (any species) per fishing set in Hawaii’s deep-set tuna longline fishery, from 2008 - 2012 (n = 12,062). Network variables account for observed homophilous groupings along ethnic lines. The E-A network is set as the base. Standard errors are clustered to account for multiple observations of 120 individual fishers.

|                         | Coefficient (β) | Robust SE | P>|z| |
|-------------------------|-----------------|-----------|-----|
| **K-A network**         | 0.187           | 0.053     | 0.000 |
| **V-A network**         | 0.217           | 0.049     | 0.000 |
| Bigeye tuna/set         | 0.000           | 0.001     | 0.807 |
| Vessel Length           | 0.005           | 0.002     | 0.012 |
| No. hooks/set           | 0.000           | 0.000     | 0.000 |
| Latitude (°N)           | 0.026           | 0.028     | 0.351 |
| Latitude2               | -0.001          | 0.001     | 0.033 |
| Longitude (°W)          | -0.231          | 0.097     | 0.017 |
| Longitude2              | -0.001          | 0.000     | 0.050 |
| Soak Time               | 0.054           | 0.010     | 0.000 |
| Temperature (F)         | -0.740          | 0.239     | 0.002 |
| Temperature2            | 0.005           | 0.002     | 0.001 |
| **Bait**                |                 |           |      |
| Sanma                   | 0.100           | 0.055     | 0.069 |
| Sardine                 | -0.080          | 0.124     | 0.518 |
| **Seasonality**         | 0.144           | 0.026     | 0.000 |
| **Lunar**               | 0.073           | 0.019     | 0.000 |
| **Year**                |                 |           |      |
| 2009                    | 0.046           | 0.069     | 0.505 |
| 2010                    | 0.203           | 0.056     | 0.000 |
| 2011                    | 0.181           | 0.055     | 0.001 |
| 2012                    | 0.093           | 0.056     | 0.099 |
| **Constant**            | 3.826           | 12.613    | 0.762 |

Wald χ²(20) 1212.230
p>|χ²| 0.000

Measures of fit

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75
Table S4.5. Are Outliers Acting More Like their Ethnic Group, or their Network Group? Full Model.

Negative binomial regression outcome testing whether outliers have significantly different rates of bycatch than their ethnic or network group. The dependent variable is shark (any species) per fishing set in Hawaii’s deep-set tuna longline fishery from 2008 – 2012 (n = 12,062). Network variables account for observed homophilous groupings along ethnic lines; outliers designate circled nodes in Fig. 4.1, which were tested against network group means. Standard errors are clustered to account for multiple observations of 120 individual fishers. The full model with outlier #57 as the base is shown; see Table 4.2 for coefficients and standard errors of remaining outliers.

| Coefficient (β) | Robust SE | P>|zl| |
|-----------------|-----------|-------|
| **A. Outlier #57, E-A with majority K-A ties (base)** |
| E-A network     | -0.171    | 0.030 | 0.000 |
| K-A network     | 0.017     | 0.055 | 0.759 |
| V-A network     | 0.047     | 0.044 | 0.292 |
| Bigeye tuna/set | 0.000     | 0.001 | 0.806 |
| Vessel Length   | 0.005     | 0.002 | 0.012 |
| No. hooks/set   | 0.000     | 0.000 | 0.000 |
| Latitude (°N)   | 0.026     | 0.028 | 0.350 |
| Latitude2       | -0.001    | 0.001 | 0.033 |
| Longitude (°W)  | -0.231    | 0.097 | 0.017 |
| Longitude2      | -0.001    | 0.000 | 0.050 |
| Soak Time       | 0.054     | 0.011 | 0.000 |
| Temperature (F) | -0.740    | 0.239 | 0.002 |
| Temperature2    | 0.005     | 0.002 | 0.001 |
| Bait            |           |       |       |
| Sanma           | 0.100     | 0.055 | 0.069 |
| Sardine         | -0.080    | 0.124 | 0.517 |
| Seasonality     | 0.144     | 0.026 | 0.000 |
| Lunar           | 0.073     | 0.019 | 0.000 |
| Year            |           |       |       |
| 2009            | 0.046     | 0.069 | 0.506 |
| 2010            | 0.203     | 0.056 | 0.000 |
| 2011            | 0.181     | 0.055 | 0.001 |
| 2012            | 0.093     | 0.056 | 0.098 |
| Constant        | 3.998     | 12.609| 0.751 |

Wald χ²(21) 1852.800
p>|χ²| 0.000

Measures of fit

| Log-likelihood intercept only | -31553.729 |
| Log-likelihood full model:   | -28851.341 |
| D(12038)                     | 57702.683 |
| LR(20)                       | 5404.775 |
| Prob > LR                    | 0.000     |
| McFadden's R2                | 0.086     |
| McFadden's Adj R2            | 0.085     |
| Maximum likelihood R2        | 0.361     |
| Cragg & Uhler's R2           | 0.363     |
| AIC                           | 4.788     |
| AIC'                          | 57750.683 |
| BIC                           | -55428.218|
| BIC'                          | -5216.819 |
References


Chapter 5
SOCIAL NETWORKS AND ECONOMIC OUTCOMES: SOCIAL CAPITAL AND FISHER PRODUCTIVITY

Abstract

There is a growing body of literature positively linking dimensions of social capital to economic performance. Yet recent research also points to a potential “dark side” of social capital, highlighting that in some cases over-embeddedness in networks and the pressures associated with brokerage can place constraints on actors, potentially having a negative effect on performance. Common-pool resource systems represent unique environments where the forewarnings of social capital's dark side are likely to be realized, i.e., information is highly valuable, stakeholders are diverse, and competition is fierce. Here, we empirically test whether social capital in the form of network prominence and brokerage plays a role in influencing the economic performance of ethnically diverse fishers competing in a complex and highly dynamic environment over limited common-pool resources. Merging several unique sets of data on vessel owners and captains from Hawaii's pelagic longline fishery in 2012, we find that network prominence has a significant, positive effect on productivity, while bridging or brokering between ethnic groups has a significant, negative effect. We also find evidence of decreasing returns to network prominence for vessel captains operating at the trip level, suggesting there is an optimal level of connectedness, beyond which the costs of adding additional ties outweigh the benefits. Our results provide novel evidence that in cases where social identities are strong and divides between groups pronounced, brokers are significantly less productive, which we argue is due to a lack of trust across groups and a penalty others place on brokers for bridging distinct social divides. Our findings also provide support to an emerging theory of nonlinear returns to network prominence by demonstrating that temporal context matters.

12 This chapter is formatted for submission to the journal Social Networks. Figure and table numbers were adjusted to align with the organization of this thesis. The full citation at present is: Barnes, M., Kalberg, K., Pan, M. and P.S. Leung. 2015. When is brokerage negatively associated with economic productivity? Ethnic diversity, competition, and common-pool resources. Working paper.
5.1 Introduction

There is a growing body of literature linking dimensions of social capital to economic performance. The social capital concept captures the idea that social bonds, and the resources embedded within them, comprise an important asset that can be leveraged for individual or collective gain (Bourdieu 1986, Coleman 1990, Lin 1999, Burt 2005). At the individual level, structural dimensions of social capital, such as network centrality and brokerage, are argued to positively affect performance by providing access and control benefits over information and resources (Granovetter 1973, Freeman 1979, Burt 1992), which is supported by a large body of empirical evidence (e.g., Burt 2002, Fafchamps and Minten 2002, Greve et al. 2010, Janhonen and Johanson 2011). Yet, recent research also points to a “dark side” of social capital, highlighting that in some cases, over-embeddedness and the pressures associated with brokerage can place constraints on actors, potentially having a negative effect on performance (Gargiulo and Benassi 1999, Krackhardt 1999, Gargiulo and Benassi 2000, Stovel and Shaw 2012, Bizzi 2013). This dichotomy suggests that context is important, yet the overwhelming majority of existing empirical evidence stems from socially homogenous populations in corporate and organizational settings, limiting a broader understanding of how context mediates the relationship between social capital and economic performance.

We live in an increasingly diverse world where immigration and migration is rapidly altering the social fabric of communities that underlie economic pursuit, particularly in the U.S. (Smith and Edmonston 1997, MacDonald and Sampson 2012). The purpose of this research is thus two-fold. First, we advance the discourse of the role of social capital on economic outcomes to a socially fragmented, ethnically diverse setting where information is highly valuable and competition is fierce. In this context, we draw on existing research in network science, sociology, psychology, and economics to theorize a positive effect of network centrality with diminishing marginal returns, and a negative affect of brokerage, where brokerage identifies ties that bridge ethnic divides. Next, we empirically test our assumptions by linking several unique datasets on a socially fragmented, ethnically diverse population of fishers operating in Hawaii’s pelagic longline fishery, where individual fishers compete in a complex and highly dynamic environment over limited common-pool resources (CPRs).

Our paper is organized as follows. The remainder of this section briefly reviews the literature on social capital and economic outcomes, extends this discussion to account for the potential
mediating effects of ethnic diversity and competition over CPRs, and introduces our research objectives and hypotheses. In section 5.2 we describe our study context. Section 5.3 introduces the diverse sets of data we leverage. Section 5.4 outlines our theoretical and empirical model, which incorporates social capital as an additional input in fisher’s production function. Section 5.5 describes our results. We discuss our results in section 5.6 and offer final concluding remarks in section 5.7.

5.1.1 Social Capital and Economic Outcomes

The social capital concept originated within the field of sociology with a focus on individuals and small groups, and the benefits accruing to them via their social relationships (Bourdieu 1986, Coleman 1988). The concept was quickly expanded by various scholars to include many aspects of social life thought to benefit individuals and communities, such as trust, shared norms and values, reciprocity, and exchanges, all of which can facilitate cooperation and collective action among actors (Nahapiet and Ghoshal 1997, Putnam 2001, Woolcock 2001). Due to this broad and sometimes vague interpretation of social capital, the concept has been plagued with controversy about its precise meaning and effects (Portes, 1998 #458). Yet to a degree there has been a consensus among scholars that social capital refers to the ability of human actors to secure benefits via membership in social structures or networks (e.g., Granovetter 1985, Portes 1998, Lin 1999, Burt 2000), however, some still argue that the concept includes not only this structural social network dimension, but also a cognitive and relational dimension comprised of shared norms/values and trust, respectively (Nahapiet and Ghoshal 1998, Tsai and Ghoshal 1998).

Acknowledging the multidimensionality of the concept, here we adopt a structural, or “networked resources” (Kadushin 2004), view of social capital. Akin to classical social resource theory (e.g., Lin 1986) and structuralist position theory (Wellman 1988), proponents of the structural view of social capital argue that social relationships comprise an important resource that can be accessed or mobilized for purposive action (Lin 1999) or competitive gain (Burt 2000), and an actor’s location in the structure of a social network can facilitate or constrain their opportunities for action (Bourdieu 1986, Coleman 1990, Lin 1999, Burt 2000). Drawing heavily from the work of Granovetter (1973), Burt (2005), Lin (1999), Wellman (2001) and others, from this perspective social capital is typically assessed by gauging the nature and extent of an individual’s interpersonal ties or their structural position within a social network.
There are various mechanisms by which aspects of social structure have been shown to produce tangible benefits, two of which are network prominence and brokerage (Fig. 5.1). The former argues that well-connected individuals centrally embedded in networks benefit from increased access to information and resources (Freeman 1979, Borgatti et al. 1998). Moreover, when surrounded by cohesive ties, they also benefit from a normative environment that facilitates trust and cooperation among actors (Coleman 1988, Coleman 1990). By their very nature, social relationships constitute information channels that can reduce the amount of time and investment necessary to gather and process information (Molina-Morales and Martinez-Fernández 2009). Social interactions can also facilitate learning through close, intensive information exchange and foster the creation and diffusion of innovations (Rogers Everett 1995, Conley and Udry 2010). Well-connected, centrally located individuals in networks have increased opportunities to capitalize on these benefits in pursuing their goals, and as such network prominence has been positively linked to economic productivity (Greve et al. 2010, Abbasi et al. 2011).

**Figure 5.1 Social Capital: Network Prominence and Brokerage.** 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 nodes are acting as brokers.

Brokerage captures the process of connecting disparate groups of actors or isolated individuals in social structures (Fig. 5.1). More formally, Stovel et al. (2011) define brokers as “intermediary links in systems of social, economic, or political relations who facilitate the trade or transmission of valued resources that would otherwise be substantially more difficult.” The authors identify two crucial defining characteristics of brokers: (1) they bridge gaps in social structure, and (2) they facilitate the transfer of goods, information, opportunities, or knowledge across these
groups. The concept of brokerage has enjoyed substantial theoretical development by Burt (1992, 2002, 2005) and his theory of “structural holes,” which emphasizes information and control advantages of occupying brokerage positions. The argument is that in connecting disparate groups, brokerage affords actors with increased access to, and control over novel and diverse information and resources, thereby enhancing the quality of benefits available to them and increasing their opportunities for action (Burt 1992). When an actor represents the sole route through which information or resources flow from one portion of a network to another, they exploit what Burt (1992) termed a “structural hole.” As a source of social capital, brokerage is typically argued to play a positive role on economic outcomes – an argument that has obtained broad support in the empirical literature across a range of organizational settings (e.g., Burt 1992, Tsai and Ghoshal 1998, Burt 2005, Abbasi et al. 2011).

5.1.2 The Dark Side of Social Capital

Though social capital has most commonly been associated with positive gains in productivity, there is growing evidence of a “dark side” of social capital in economic settings (Gargiulo and Benassi 1999). As demonstrated in the previous section, being well connected and centrally located in social structures clearly has its advantages. Yet recent research also cautions against being “over-embedded” or too central in networks (Uzzi 1997, Aral and Van Alstyne 2007, Ferriani et al. 2009, Molina-Morales and Martínez-Fernández 2009). With more social relationships comes increasing coordination costs, as more time and energy is devoted to maintaining them (Ferriani et al. 2009). Because time and energy are clearly exhaustible resources, increasing social ties beyond a certain point is likely to result in diminishing returns (McFadyen and Cannella 2004). Moreover, as actors become more central in networks, they are faced with larger inflows of information and bear greater cognitive pressures associated with processing it (Dodds et al. 2003), potentially resulting in “information overload” (Schneider 1987, Ferriani et al. 2009). In economic settings, actors suffering from information overload risk losing perspective and can have trouble distinguishing between relevant and irrelevant information, ultimately resulting in poor decision-making (Schneider 1987). Indeed, evidence of diminishing marginal returns associated with being well connected in knowledge and information sharing networks has recently been demonstrated in several recent studies (Aral and Van Alstyne 2007, Ferriani et al. 2009, Molina-Morales and Martínez-Fernández 2009).
Perhaps even more compelling is the emerging literature on the tenuous nature of brokerage (Bizzi 2013), the theory of which, until recently, had largely overlooked its fragile nature and the contextual conditions under which gains from brokerage can be expected (Stovel et al. 2011). Aside from the strict focus on structural holes, opportunities for brokerage can be captured by directly examining tie diversity or ties that link different types or subgroups of actors (Barnes-Mauthe et al. 2014), which corresponds to Granovetter’s (1973) strength of weak ties argument and to what Borgatti et al. (1998) describe as network heterogeneity. In settings where there are closely aligned subgroups or strong homophilic tendencies, where individuals primarily interact solely with others similar to themselves along some trait or set of traits, information and resources can become highly centralized and homogenous within groups (McPherson et al. 2001). Thus, individuals who effectively span these groups “bridge” social divides, which, according to the dominant theory, should enhance their ability to tap diverse sources of knowledge and gain access to a greater variety of resources.

According to the common interpretation of the work of Burt (1992), such brokerage should be positively associated with economic advantage. Yet, in recent work, Stovel and colleagues (2011, 2012) argue that there are inherent tensions involved in occupying brokerage positions – tensions which sociological theory suggest may actually constrain actors. Notably, in accordance with balance theory, the authors caution that when social networks are highly clustered and an “us-them” world emerges, which is famously associated with network homophily (McPherson et al. 2001), brokers are likely to face strong conflicting pressures to commit to one group or the other, or endure social exclusion. The constraining nature of having a foot in two social worlds had previously been highlighted by Krackhardt (1999) in his work on simmelian ties, where he too warned of the normative pressure of groups which may overpower the advantages of brokerage. Actors who bridge cohesive subgroups also risk suffering from role conflict (Goffman 1959), which can cast suspicion on their loyalties and commitment and generate severe distrust from actors on both sides of the divide (Bailey 1963, Stovel et al. 2011, Stovel and Shaw 2012). As such, Stovel and Shaw (2012) conclude that the character of brokerage is likely intimately connected to the macro-level structure of time and place. It follows that in some cases, not only are gains from brokerage unlikely, but brokers may in fact suffer negative economic consequences. We suspect that this may particularly be expected under conditions of competition, where critical information and resources are likely withheld from brokers for fear of them being shared with other groups.
5.1.3 Social Capital, Ethnic Diversity, and Common-Pool Resources

Common-pool resource (CPR) systems represent unique environments where the forewarnings of social capital’s dark side are likely to be realized – perhaps particularly in ethnically diverse settings. CPR systems have two defining characteristics that set the stage for a highly competitive environment: nonexcludability and rivalry. Nonexcludability refers to the fact that excluding individuals from extracting or otherwise benefiting from the resource through any physical and/or institutional means is either impossible or impractical (i.e., the system exhibits an ‘open access’ characteristic), while rivalry defines resources in which exploitation by one user reduces resource availability for others (Ostrom et al. 1994). Under classic economic theory, which assumes a rational individual acting in his or her own self-interest, actors in CPRs will overinvest in resource extraction and attempt to extract the resource at a rapid rate (i.e., before others do), free-ride off the efforts of others, and choose to defect from attempts at cooperative arrangements (Gordon 1954, Scott 1955, Hardin 1968, Schlager 2002). As Schlager (2002) states, “in such situations, individual rationality results in collective irrationality” (p. 802), where individuals following their own short-term interests produce outcomes that are not in anyone’s long-term interest (Ostrom et al. 1999).

Though the theory of the rational, self-interested, and non-cooperative actor in CPR settings has wide theoretical and empirical support and has been the foundation of formal models (e.g., Gordon 1954, Scott 1955, Hardin 1968), recent research has emphasized that actors in CPR settings are sometimes (perhaps unexpectedly) cooperative and “pro-social” (Ostrom 1990, Gintis 2000). For example, in their seminal paper, Akerlof and Kranton (2000) present a model of identity-based utility, where one’s identity, or sense of self, which is considered in relation to social categories or groups, can have a strong affect on individual behavior and resulting economic outcomes. In line with the social identity theory (Tajfel and Turner 1979), identifying with groups affords actors with benefits from group membership. As such, they may align their behavior in accordance with perceived group norms, even at the expense of their own self-interest. In ethnically diverse settings characterized by strong homophily and fragmentation, group identities can cause individuals to accentuate their differences with others. Such behavior can augment conflict, decrease trust (Baerveldt et al. 2004), and generally result in discriminatory behavior across groups (Tajfel and Turner 1979) – a phenomena thought to be

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13 Pro-social behavior can be defined as social behavior that benefits other people or society as a whole.
inflated under conditions of competition over scarce resources (Poteete and Ostrom 2004). Many CPR systems are also incredibly complex with multiple components operating across various spatial and temporal scales, thus the threat of information overload on decision-making in this context cannot be disregarded. Thus, in CPR systems plagued with strong homophily along ethnic lines, though being well (but not overly) connected within groups may provide tangible benefits for economic actors, we suspect that brokerage may result in negative net returns due to a suspicion over their loyalties and a general mistrust of their interaction with other groups.

5.1.4 Hypotheses

Bringing together the insights on social capital, balance, role conflict, social identify, and economic action discussed in sections 5.1.1 – 5.1.3, here we examine the role of network prominence and brokerage on individual economic outcomes in a competitive, ethnically diverse CPR system characterized by strong homophily. To accomplish this, we leverage multiple datasets on a population of vessel owners and captains, including comprehensive information sharing network data, to examine social capital effects using explicit sociometrics. Our analysis is conducted in a unique setting, i.e., a competitive CPR system characterized by a heterogeneous population with clear divides across ethnic groups, many of which are comprised of first generation immigrants. In this context, we hypothesize that social capital plays a strong role in influencing fisher productivity. Specifically, we propose the following specific hypotheses:

**H1**: Fisher’s with greater access to information via trusted contacts within their local social network (i.e., network prominence) will have higher levels of productivity up to a certain point, after which they will experience diminishing marginal returns.

**H2**: Brokerage, defined as ties that bridge ethnic groups, will be negatively associated with economic productivity due to high levels of competition, a lack of trust across ethnic divides, and an underlying suspicion of those who interact across these divides.
5.2 Study Context: Hawaii’s Longline Fishery

Hawaii’s longline fishery (HLF) is a limited-entry, multimillion-dollar industry supplying domestic and international markets with fresh tuna and swordfish, and is the largest commercial fishing sector in the Hawaiian Islands (Fig. 5.2). The fishery is described in detail in Chapter 2.

Pelagic marine fisheries are highly dynamic and complex, covering vast spatial scales and subject to spatiotemporal dynamics that often fluctuate in unpredictable ways (Wilson 1990). Due to this complexity and the dynamic nature of the open ocean, individual fishers operate in a heterogeneous environment and are faced with a high level of uncertainty on a daily basis. Decision-making in this context is also shaped by an array of socio-political processes. In addition to other strict regulations, HLF is managed under a total allowable catch (TAC) on bigeye tuna assigned by international fishery management organizations. Bigeye tuna is currently classified as experiencing overfishing in the Western and Central Pacific Ocean (WCPO) and Eastern Pacific Ocean (EPO), meaning the rate of removal exceeds levels which could be reasonably assumed to be sustained in the long-term.\(^{14}\) If the TAC is reached the fishery has to be shut down. This typically occurs toward the end of the calendar year, which overlaps with the busy holiday season when fresh tuna is in high demand throughout the Hawaiian Islands. In addition, the fishery is subject to an annual sea turtle interaction cap intended to protect vulnerable and endangered sea turtle populations, which primarily affects shallow-set swordfish trips, as sea turtles are more often incidentally caught at shallower depths. Fishery management regulations are reviewed and updated every three years by the Western and Central Pacific Fisheries Commission and Inter-American Tropical Tuna Commission, the regional fishery management organizations (RFMOs) that are responsible for the conservation and management of tuna and other marine resources in the WCPO and EPO.

\(^{14}\) Bigeye tuna is a very popular high-value product and is one of the primary species targeted in the WCPO. Due to high demand and the exponential growth of fishing capacity, bigeye tuna stocks have been continually declining over the past decade, similar to other high-value predatory species. The most recent stock assessment has officially classified bigeye in the WCPO as experiencing overfishing and approaching an overfished state, with total spawning and biomass having declined to about half of their initial levels in the mid-1970s. Though the majority of adult bigeye tuna in the WCPO is targeted and harvested by longline fleets originating from across the Pacific, the past 30 years has seen an exponential increase in the capacity of purse seine fleets due to advancements in technology, such as the development of fish aggregating devices, which is significantly contributing to a reduction in bigeye tuna biomass through the incidental catch of juveniles. Both longline fisheries and purse seine fisheries operating in the WCPO are under the jurisdiction of the Western and Central Pacific Fisheries Commission, and all bigeye tuna caught in the WCPO is managed as one stock, regardless of the landing location or gear deployed.
respectively. The vast majority of individual fishers operating in Hawaii’s longline fleet have little to no direct interaction with (or influence over) decisions made by RFMOs.

HLF is thus characterized by repetitive and competitive interactions among individual fishers, who compete over limited CPRs in a dynamic and uncertain environment. The production process under these conditions is rather unique because acting as “firms,” fishers must determine the most strategic use of inputs over time and space to transform wild and highly mobile stocks of fish into catch, all while accommodating their activities to the socio-political environment and the spatiotemporal dynamics of the open ocean. In this setting, there are several means by which network prominence and brokerage may influence fisher performance; chief among them is the role of information sharing.

The value of information in competitive fisheries has been well documented (Mangel and Clark 1983, Rudd 2001, Salas and Gaertner 2004, Dreyfus-Leon and Gaertner 2006, Gezelius 2007) and information access and management is especially important when dealing with aggregated migratory resources such as schools of tuna. Specifically, there are two types of information that can enhance decision making in this context: short-run information, such as information on the location of species, which would be valuable for vessel captains; and long-run information, such as information on technical/economic innovations, which would be valuable for vessel owners. Though the rational actor model suggests that fishers acting in their own self-interest are unlikely to share such information due to its potential to increase the efficiency of others, thereby decreasing resource availability, Barnes-Mauthe et al. (2013, 2014) provide compelling evidence to the contrary. Specifically, in their investigation of information sharing networks in HLF, the authors found a surprisingly high level of social interaction. An average of 9.28 information sharing ties pertaining to both short-run and long-run topics were reported per actor, with the majority of fishers sharing information at least 1-3 times per week (Barnes et al. 2012). This implies it is common for fishers to communicate with each other within fishing trips, as the average trip length in 2012 was approximately 22.5 days. The authors thus conclude that in sharing information, fishers are reacting to the problem of uncertainty by learning from each other, which is likely to affect their performance in transforming wild fish into catch (Barnes et al. 2012). Indeed, recent research suggests that fishers occupying central positions within their social network and working together rather than alone are more likely to be successful when targeting highly mobile species (Mueller et al. 2008). Simulation studies have also shown that
captains belonging to efficient fisher ‘code groups’ have a greater probability of locating concentrations of tuna than isolated fishers (Dreyfus-Leon and Gaertner 2006).

Despite a surprisingly high level of cooperative information sharing ties generally present in HLF, Barnes-Mauthe et al. (2013) found the overwhelming majority of ties fell within strict ethnic boundaries. As described in Chapter 2, despite Hawaii’s diverse multicultural background (Nordyke 1989), the HLF is comprised of only three distinct ethnic groups: a group of Vietnamese-Americans (V-A), European-Americans (E-A), and Korean-Americans (K-A), and communication among fishers within ethnic groups is significantly more extensive than between groups (Fig. 2.2). The homophily effect is strong and has a substantial impact on the overall structure of the network, and low levels of trust across groups have been documented (Barnes-Mauthe et al. 2013, Barnes-Mauthe et al. 2014).  

### 5.3 Data

To assess the role of social capital on fisher productivity we linked several different datasets, including: social network data; annual cost-earnings data; NOAA National Marine Fisheries Service (NMFS) federal logbook, observer, and trip expenditure data; and Hawaii Department of Agriculture (HDAR) dealer data; each described in turn.

#### 5.3.1 Social Network Data

Social network data was collected by Barnes-Mauthe et al. (2013), and includes detailed data on information sharing relationships of over 90% of all vessel captains and owners thought to be active during data collection ($n = 143$), which occurred from May 2011 – January 2012. Respondents were first asked whether or not they frequently discuss or share valuable information regarding different aspects of fishing with other stakeholders in the fishery. Respondents were then asked to identify information sharing relationships with up to 10 individuals. Subsequently, respondents disclosed which information sharing topic(s) were discussed with each actor from a predetermined list of topics identified by key informants as

---

15 Existing quantitative and qualitative research strongly suggests that ethnicity plays the dominant role in influencing the network homophily effect and the overall structure of HLF information sharing network over all other fisher attributes, such as age, title, education and experience (Davies et al. 2011).

16 The original dataset included 145 respondents, two of which were dropped due to incomplete information.
important for both long-run and short-run decision making. Short-run information sharing topics included fish activity (i.e., “what the fish are doing”), site catch/set location (where the fish are), bycatch (which is preferably avoided), and weather. Long-term information sharing topics included vessel technology, hiring of captain or crew, fishery regulations, and gear maintenance. Respondents often named other fishers as important for information sharing, but also identified a number of industry leaders and government/management officials. Though all persons identified as important for information sharing are included in the resulting networks, respondents were limited to economic actors/primary decision-makers, defined as vessel owners and captains. The survey also collected detailed information on socio-demographics and was fielded in person with the help of Vietnamese and Korean interpreters as needed. The network data is described in greater detail in Chapter 2.

5.3.2 Annual Cost-Earnings Data

In collaboration with NOAA’s Pacific Islands Fisheries Science Center (PIFSC) Economics Program, detailed information on vessel operating costs was collected from vessel owners and operators through a structured cost-earnings survey focused on annual fixed costs incurred during the 2012 calendar year (see Kalberg and Pan 2014). The survey was fielded in person with the help of Vietnamese and Korean interpreters from January – September 2013.

5.3.3 Trip Expenditure Data

Trip-level variable costs are continuously collected on a volunteer basis on all federally observed trips through the ongoing Hawaii Longline Trip Expenditure Study, a joint effort between the PIFSC Economics Program and the Pacific Islands Regional Office (PIRO) Observer Program (Pan et al. 2014). All shallow-set swordfish trips and 20% of deep-set tuna trips originating in Hawaii are federally mandated to carry an onboard fishery observer that collects detailed data on catch and effort. Trip-level expenditure data was voluntarily provided through this mechanism on 60% of all observed trips in 2012. Using this sample set of trip cost data, a regression model was developed to estimate a trip cost function in relation to individual vessel and trip characteristics, such as vessel length, number of sets, trip length, and travel distance in order to generate cost information for trips that did not provide explicit expenditure data (see Kalberg and Pan 2014).

5.3.4 Hawaii Department of Aquatic Resources Dealer and Logbook Data
Detailed sales records, including number of fish sold, price per pound, weight, and value, pertaining to H are regularly collected through Hawaii Department of Aquatic Resources (HDAR) dealer reports. We directly acquired trip revenue data from these HDAR dealer reports for all longline trips landed in Hawaii in 2012. In 2012 there were also a handful of trips that landed their catch outside of Hawaii, resulting in a record of catch and effort present in the NMFS federally mandated logbooks, but not accounted for in the HDAR dealer reports. For these trips, HDAR dealer data was used to calculate average weekly fish prices and average weight by species, which was multiplied by the number of each species recorded as kept 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 2014).

5.3.5 Data Compilation

Cost-earnings data, trip expenditure data, and HDAR dealer and logbook data was integrated using vessel permit numbers or vessel names and landing dates, trip return dates, and sales data. Information on vessel ownership during the 2012 calendar year was collected via the social network survey, which was used to link social network data on vessel owners to their respective vessels. Captains were linked to each trip using a combination of fishery observer data, which identified operators on every observed trip, and information from the social network survey, where vessel operators reported all vessels they had operated within the last five years. The data was stripped of all names and other personally identifying information immediately after the data was merged in accordance with confidentiality agreements.

5.4 Methods

5.4.1 The Production Function Model

17 It is common for Hawaii-based vessels to land catch from swordfish trips during the winter months when swordfish migration is further east. Based on personal communications with swordfish longliners that land in California, swordfish prices in California are similar to those in Hawaii, but the distance is shorter to the west coast, thus fuel cost are lower.

18 Average auction prices for the same species often vary significantly between vessels due to fishing grounds, fish handling practices of the vessel, and by the average time between landings and sales. Fish size can also vary substantially.
To test our claim that social capital plays a strong role in influencing fishers’ economic productivity, we follow similar approaches found in the literature (e.g. Fafchamps and Minten 2002) by incorporating social capital as an added input in the production function. The general production function is

\[ Y = F(L,K) \]  

(5.1)

where \( Y \) denotes total production, \( L \) is labor input, and \( K \) is capital input. In specifying a production function for Hawaii’s longline fishers, we can distinguish physical from both human and social capital following Fafchamps and Minten (2002). 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), social capital \( S \) (centrality, brokerage), and vessel and owner/operator specific characteristics \( Z \) (vessel size, vessel age, target species, ethnicity, etc.). Equation 5.1 can therefore be re-specified as,

\[ Y = F(L,K,H,S,Z) \]  

(5.2)

Here, we are specifically interested in social capital, \( S \). If social capital is irrelevant to fisher’s production process, \( S \) should have no effect on output when controlling for \( L, K, H, \) and \( Z \). Yet we hypothesize that when controlling for other factors of production, centrality, \( S_c \), will have a positive effect on \( Y \), while brokerage, \( S_b \), will have a negative effect. Our general empirical model is therefore specified as,

\[
\ln(Y) = \beta_0 + \alpha_1 \ln(L) + \sum_{n=1}^{N} \alpha_n \ln(K_n) + \beta_{1} H_{ed} + \beta_{2} \ln(H_{exp}) + \beta_{3} \ln(S_c) + \beta_{4} \ln(S_b) + \sum_{n=1}^{N} \beta_{n} Z_n \quad (5.3)
\]

where \( Y \) denotes gross revenue, \( L \) represents crew size, \( K \) corresponds to various capital inputs described in Table 5.1, \( H_{ed} \) is a dummy variable for education (some college or higher), \( H_{exp} \) denotes years of fishing experience, \( S \) are the same as described above, and \( Z \) denotes various vessel and operator specific variables described in Table 5.1. Though using gross revenue instead of a quantity as the output results is not truly a production function, catches in HLF typically feature multiple species that receive different market prices, thus the use of aggregated quantity of fish landed is not a suitable measure of output. In multi-product firms such as these, the use of values has been standard practice in empirical work (Pradhan et al. 2003).
To assess the role of social capital on fisher productivity, we estimated two simple, separate production functions: one for vessel owners at the annual level, and one for vessel captains at the trip-level. Both analyses correspond to the 2012 calendar year.

Table 5.1 Description of Input, Vessel, and Operator Specific Variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Capital and labor</strong></td>
<td></td>
</tr>
<tr>
<td>Trip days</td>
<td>Total trip length (in days), including days spent on travel</td>
</tr>
<tr>
<td>Crew size</td>
<td>Number of persons on the boat, including the captain</td>
</tr>
<tr>
<td>Fixed cost</td>
<td>Annual fixed operating costs ($/yr), including dry dock, engine work, technology upgrades, and continuous maintenance</td>
</tr>
<tr>
<td>Variable cost</td>
<td>Annual variable operating costs ($/yr), i.e., total annual trip-level costs, including fuel, bait, ice, and other miscellaneous items (used in vessel owner analysis)</td>
</tr>
<tr>
<td>Other input</td>
<td>Trip-level variable operating costs ($/trip), including fuel, bait, ice, and other miscellaneous items (used in vessel captain analysis)</td>
</tr>
<tr>
<td><strong>Human capital</strong></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>Value 1 if the owner or operator had some college education, 0 otherwise</td>
</tr>
<tr>
<td>Experience</td>
<td>Owner or operator's fishing experience (years)</td>
</tr>
<tr>
<td><strong>Social capital</strong></td>
<td></td>
</tr>
<tr>
<td>Indegree centrality</td>
<td>Number of incoming ties identified as important for sharing long-run information (owners); number of incoming ties identified as important for sharing short-run information (captains)</td>
</tr>
<tr>
<td>Bridging ties</td>
<td>Total number of inter-ethnic ties in the long-run information sharing network (owners); total number of inter-ethnic ties in the short-run information sharing network (captains)</td>
</tr>
<tr>
<td><strong>Vessel specific variables</strong></td>
<td></td>
</tr>
<tr>
<td>Target: swordfish</td>
<td>Value 1 if the vessel targeted swordfish for at least 1 trip in 2012, 0 otherwise (targeted tuna only)</td>
</tr>
<tr>
<td>Vessel age</td>
<td>Age of vessel as of 2013</td>
</tr>
<tr>
<td>Vessel size: small</td>
<td>Value 1 if the vessel is a small size ($\leq$ 55 feet), 0 otherwise</td>
</tr>
<tr>
<td>Vessel size: medium</td>
<td>Value 1 if the vessel is a medium size (&gt;55 feet and &lt;74 feet), 0 otherwise</td>
</tr>
<tr>
<td><strong>Owner specific variables</strong></td>
<td></td>
</tr>
<tr>
<td>Owner-operated</td>
<td>Value 1 if the vessel was owner-operated, 0 otherwise (hired captain)</td>
</tr>
<tr>
<td>Ethnicity: E-A</td>
<td>Value 1 if the owner/operator is European-American, 0 otherwise</td>
</tr>
<tr>
<td>Ethnicity: K-A</td>
<td>Value 1 if the owner/operator is Korean-American, 0 otherwise</td>
</tr>
</tbody>
</table>

5.4.2 Social Capital Input
To measure social capital, we employed structural measures of prominence and brokerage, namely, indegree centrality and number of inter-ethnic ties. Degree centrality is a simple measure of local centrality that measures the number of edges (i.e., ties) a node has in a network. In a directed network, where information on the direction of the tie (either outgoing or incoming) is available, degree centrality can be distinguished between indegree, representing ties coming into an actor, and outdegree, representing ties going out from an actor. We employed indegree centrality rather than outdegree for two reasons. First, due to the competitive nature of fishing and the value of information, we suspect that incoming ties more accurately indicate the potential benefits of network prominence due to a baseline level of trust that is associated with others nominating particular actors as important contacts. Second, outdegree was capped in our survey instrument, inherently limiting its variation and ability to truly identify well connected actors. Due to the strong homophily effect along ethnic lines, we conceptualized brokerage as the number of inter-ethnic ties, which is in line with existing research on HLF (Barnes-Mauthe et al. 2013, Barnes-Mauthe et al. 2014).

We generated indegree centrality and brokerage metrics using two separate networks for vessel owners and captains (Fig. 5.2). For vessel owners, we constructed a long-run network consisting of ties identified by all respondents as important for sharing 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 shared with each person they nominated (very valuable, somewhat valuable, not valuable). Ties designated “not valuable” were dropped. 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 included 167 nodes, 781 ties, 119 reciprocal ties, 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\(^\text{19}\) (Fig. 5.2).

\(^{19}\) The homophily index is calculated as the number of ties external to groups minus the number of ties internal, divided by the total number of ties possible. This results in a value of +1, indicating extreme heterophily, to -1, indicating extreme homophily.
Figure 5.2 Graphical Depictions of (A) Vessel Owner’s Long-Run Information Sharing Network and (B) Vessel Captain’s Short-Run Information Sharing Network. Long-run ties are used to access and share information on vessel technology, hiring captain or crew, gear maintenance, and fishing regulations. Short-run ties are used to access and share information on fish activity, site catch/set location, bycatch, and weather. Each shape or node represents an actor in the network, and the lines or edges connecting them represent their information-sharing ties. The network was created in NetDraw 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.
For vessel captains, we constructed a short-run network consisting of ties identified by all respondents as important for sharing 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 resulting network included 158 nodes, 620 ties, 74 reciprocal 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. 5.2).

5.4.3 Other Inputs

Explanatory variables used in vessel owner’s production function differed slightly from that of vessel captains, primarily due to the difference in scale at which the production process was estimated (see Tables 5.2 and 5.3). Specifically, vessel owner’s production functions were estimated at the annual level accounting for all trip days, inputs, and total annual revenue, whereas captain’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, communication, and lightsticks for swordfish trips. Only trip-level costs were included in captain’s production functions (denoted as other inputs). Captain’s production functions also included a squared term for trip days term to account for the potentially negative effect of “lost” time or spending too long at sea (e.g., engine trouble, poor weather extending the search time, etc.), as the quality of fresh fish and it’s corresponding market price is expected to decrease from the time it is caught until it reaches the market.

5.4.4 Sample

The compiled data described in Section 5.3 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 generate vessel owner’s production function. 15% of these vessels targeted swordfish for at least one trip during the year, while the other 85%
targeted bigeye only. Summary statistics for the 2012 annual-level data included in the production function are presented in Table 5.2.

Table 5.2 Summary Statistics for Vessel Owner's Production Function Inputs, 2012.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Mean</th>
<th>Std. dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output (annual revenue)</td>
<td>USD</td>
<td>$758,062.30</td>
<td>$275,751.80</td>
</tr>
<tr>
<td><strong>Capital and labor</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trip days</td>
<td>days/yr</td>
<td>254.703</td>
<td>210.991</td>
</tr>
<tr>
<td>Crew size</td>
<td>no. of persons</td>
<td>5.810</td>
<td>0.710</td>
</tr>
<tr>
<td>Fixed cost</td>
<td>$/yr</td>
<td>$98,734.49</td>
<td>$36,845.37</td>
</tr>
<tr>
<td>Variable cost</td>
<td>$/yr</td>
<td>$343,420.10</td>
<td>$102,752.60</td>
</tr>
<tr>
<td><strong>Human capital</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>some college or above = 1</td>
<td>0.495</td>
<td>0.503</td>
</tr>
<tr>
<td>Experience</td>
<td>years fishing</td>
<td>27.962</td>
<td>12.215</td>
</tr>
<tr>
<td><strong>Social capital</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indegree centrality</td>
<td>no. of incoming ties</td>
<td>12.044</td>
<td>14.705</td>
</tr>
<tr>
<td>Bridging ties</td>
<td>no. of inter-ethnic ties</td>
<td>1.802</td>
<td>2.177</td>
</tr>
<tr>
<td><strong>Vessel specific variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Target: swordfish</td>
<td>yes = 1</td>
<td>0.154</td>
<td>0.363</td>
</tr>
<tr>
<td>Vessel age</td>
<td>years</td>
<td>27.846</td>
<td>10.421</td>
</tr>
<tr>
<td>Vessel size: small</td>
<td>yes = 1</td>
<td>0.099</td>
<td>0.3</td>
</tr>
<tr>
<td>Vessel size: medium</td>
<td>yes = 1</td>
<td>0.44</td>
<td>0.499</td>
</tr>
<tr>
<td><strong>Owner specific variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Owner-operated</td>
<td>yes = 1</td>
<td>0.352</td>
<td>0.48</td>
</tr>
<tr>
<td>Ethnicity: E-A</td>
<td>yes = 1</td>
<td>0.374</td>
<td>0.486</td>
</tr>
<tr>
<td>Ethnicity: K-A</td>
<td>yes = 1</td>
<td>0.165</td>
<td>0.373</td>
</tr>
</tbody>
</table>

For vessel captain’s production function at the trip-level, we evaluated shallow-set swordfish trips separately from deep-set tuna trips because they consisted of different fishing profiles. The trip-level data for 2012 included 984 recorded tuna trips, 40 of which were taken by captains not present in the network data. An additional 37 trips were missing key variables, resulting in a total usable sample of 907 deep-set tuna trips taken by 84 vessel captains 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 V-A,
and there was very little variation in their patterns of information sharing or vessel operating characteristics. Our analysis on vessel captains therefore focuses on deep-set tuna targeting trips only. Note that all captains operating vessels on swordfish trips also participated in tuna trips during the 2012 calendar year. Summary statistics for the trip-level data included in the production function are presented in Table 5.3.

Table 5.3 Summary Statistics for Vessel Captain’s Production Function Inputs, 2012.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Mean</th>
<th>Std. dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output (trip revenue)</td>
<td>USD</td>
<td>$67,739.81</td>
<td>$33,606.92</td>
</tr>
<tr>
<td><strong>Capital and labor</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trip days</td>
<td>days/trip</td>
<td>22.535</td>
<td>5.408</td>
</tr>
<tr>
<td>Crew size</td>
<td>no. of persons</td>
<td>4.682</td>
<td>0.672</td>
</tr>
<tr>
<td>Other input</td>
<td>$/trip</td>
<td>$29,683.97</td>
<td>$8,797.28</td>
</tr>
<tr>
<td><strong>Human capital</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>some college or above = 1</td>
<td>0.258</td>
<td>0.438</td>
</tr>
<tr>
<td>Experience</td>
<td>years fishing</td>
<td>24.759</td>
<td>9.218</td>
</tr>
<tr>
<td><strong>Social capital</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indegree centrality</td>
<td>no. of incoming ties</td>
<td>4.026</td>
<td>4.455</td>
</tr>
<tr>
<td>Bridging ties</td>
<td>no. of inter-ethnic ties</td>
<td>0.584</td>
<td>0.93</td>
</tr>
<tr>
<td><strong>Vessel specific variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vessel age</td>
<td>years</td>
<td>26.498</td>
<td>10.113</td>
</tr>
<tr>
<td>Vessel size: small</td>
<td>yes = 1</td>
<td>0.134</td>
<td>0.341</td>
</tr>
<tr>
<td>Vessel size: medium</td>
<td>yes = 1</td>
<td>0.406</td>
<td>0.491</td>
</tr>
<tr>
<td><strong>Owner specific variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Owner-operated</td>
<td>yes = 1</td>
<td>0.328</td>
<td>0.470</td>
</tr>
<tr>
<td>Ethnicity: E-A</td>
<td>yes = 1</td>
<td>0.409</td>
<td>0.492</td>
</tr>
<tr>
<td>Ethnicity: K-A</td>
<td>yes = 1</td>
<td>0.196</td>
<td>0.397</td>
</tr>
</tbody>
</table>

5.5 Results

The estimation of two production functions for vessel owners by ordinary least squares are presented in Table 5.4. In the first model we test indegree centrality and brokerage as measures of social capital, while in the second model we also test the hypothesis of diminishing marginal
returns to indegree centrality by including its squared term (where a significantly negative coefficient of the squared term indicates diminishing marginal returns). In both models, brokerage is highly significant and negative, as hypothesized. Indegree centrality is positive and highly significant in model 1, yet our hypothesis of diminishing marginal returns is not supported. This is clear when examining the results of model 2, which show that the squared term for indegree centrality is positive and insignificant. Since there is no difference in the adjusted $R^2$ between model 1 and model 5.2, we conclude that model 1 most accurately estimates the annual level production function for vessel owners.

Table 5.4 Effect of Social Capital on Vessel Owner Annual Revenue, 2012 ($n = 91$).

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th></th>
<th>Model 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>unit</td>
<td>Coef</td>
<td>SE</td>
<td>Coef</td>
</tr>
<tr>
<td><strong>Capital and labor</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trip days</td>
<td>log</td>
<td>0.897***</td>
<td>0.204</td>
<td>0.965***</td>
</tr>
<tr>
<td>Crew size</td>
<td>log</td>
<td>0.229</td>
<td>0.227</td>
<td>0.253</td>
</tr>
<tr>
<td>Fixed cost</td>
<td>log</td>
<td>0.077</td>
<td>0.065</td>
<td>0.104</td>
</tr>
<tr>
<td>Variable cost</td>
<td>log</td>
<td>0.315*</td>
<td>0.180</td>
<td>0.283</td>
</tr>
<tr>
<td><strong>Human capital</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>yes</td>
<td>-0.050</td>
<td>0.057</td>
<td>-0.065</td>
</tr>
<tr>
<td>Experience</td>
<td>log</td>
<td>0.107**</td>
<td>0.043</td>
<td>0.103**</td>
</tr>
<tr>
<td><strong>Social capital</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indegree centrality</td>
<td>log</td>
<td>0.124***</td>
<td>0.037</td>
<td>0.052</td>
</tr>
<tr>
<td>Indegree centrality$^2$</td>
<td>log</td>
<td></td>
<td>0.020</td>
<td>0.022</td>
</tr>
<tr>
<td>Bridging ties</td>
<td>log</td>
<td>-0.158***</td>
<td>0.043</td>
<td>-0.168***</td>
</tr>
<tr>
<td><strong>Vessel specific variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Target: swordfish</td>
<td>yes</td>
<td>-0.130*</td>
<td>0.076</td>
<td>-0.131*</td>
</tr>
<tr>
<td>Vessel age</td>
<td>level</td>
<td>-0.006**</td>
<td>0.003</td>
<td>-0.007***</td>
</tr>
<tr>
<td>Vessel size: small</td>
<td>yes</td>
<td>-0.158</td>
<td>0.111</td>
<td>-0.131</td>
</tr>
<tr>
<td>Vessel size: medium</td>
<td>yes</td>
<td>-0.059</td>
<td>0.064</td>
<td>-0.052</td>
</tr>
<tr>
<td><strong>Owner specific variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Owner-operated</td>
<td>yes</td>
<td>-0.124**</td>
<td>0.054</td>
<td>-0.113**</td>
</tr>
<tr>
<td>Ethnicity: E-A</td>
<td>yes</td>
<td>0.164**</td>
<td>0.075</td>
<td>0.188**</td>
</tr>
<tr>
<td>Ethnicity: K-A</td>
<td>yes</td>
<td>-0.032</td>
<td>0.095</td>
<td>-0.020</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>level</td>
<td>3.019**</td>
<td>1.379</td>
<td>2.765*</td>
</tr>
</tbody>
</table>

$R^2$: 0.827, 0.829

Adj. $R^2$: 0.792, 0.792

*, **, *** denotes significance at the 0.10, 0.05, and 0.01 level.
Results regarding other inputs are largely in accordance with expectations. Capital and labor (trip day, crew size, fixed cost, and variable cost) have the correct sign, though only trip days and variable cost are significant. On the human capital side, experience is shown to boost productivity, while education plays a negative, but non-significant role. Fishers that switch from fishing swordfish to fishing tuna do significantly less well in terms of generating revenue at the annual level, as do those with older vessels, as expected. Surprisingly, vessel size does not appear to play a major role in influencing productivity, and owners who also operate their vessel are significantly less productive. Results also show that overall, when controlling for other variables, E-A fishers generate significantly more revenue than others. The explanatory power of the model is high ($R^2 > 0.82$).

The estimation of two production functions for vessel captains by ordinary least squares are presented in Table 5.5. As in the owner models, model 1 includes indegree centrality and brokerage as measures of social capital, while model 2 also includes the squared term for indegree centrality. Brokerage is highly significant and negative in both models, in line with our hypothesis. Indegree centrality is positive but not significant in model 1, yet our hypothesis of diminishing marginal returns is supported in this case. Specifically, in model 2 indegree centrality is positive and significant and its squared term is negative and significant. Moreover, the adjusted $R^2$ rose from 0.39 to 0.40 with the addition of the squared term, indicating that in this case model 2 most accurately estimates the trip level production function for vessel captains.

Results regarding capital and labor are largely in accordance with expectations, though labor is not significant. All capital variables have the expected sign and are highly significant, including the squared term for trip days, which captures the diminishing marginal returns of remaining at sea for too long. Results from human capital are mixed. Experience is positive but not significant, yet our results show a strong negative relationship between education and productivity. As was the case with vessel owners, fishers with older vessels perform less well. Here, vessel size does matter, with both small and medium sized vessels generating more revenue on average than larger vessels, which may be explained by the higher fuel costs that larger vessels endure. Both owning and operating your vessel does not appear to play a major role in influencing trip-level revenue. Similar to results for vessel owners, our results show that when controlling for other variables, E-A fishers generate significantly more revenue at the trip level than others, yet in this case, K-A fishers are significantly less productive.
Table 5.5 Effect of Social Capital on Vessel Captain Trip-Level Revenue, 2012 ($n = 853$).

<table>
<thead>
<tr>
<th></th>
<th>Unit</th>
<th>Coef</th>
<th>SE</th>
<th>Coef</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Capital and labor</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trip days</td>
<td>log</td>
<td>8.835***</td>
<td>0.835</td>
<td>9.014***</td>
<td>0.834</td>
</tr>
<tr>
<td>Trip days2</td>
<td>log</td>
<td>-1.453***</td>
<td>0.147</td>
<td>-1.467***</td>
<td>0.147</td>
</tr>
<tr>
<td>Crew size</td>
<td>log</td>
<td>0.222</td>
<td>0.179</td>
<td>0.193</td>
<td>0.180</td>
</tr>
<tr>
<td>Other input</td>
<td>log</td>
<td>0.830***</td>
<td>0.145</td>
<td>0.823***</td>
<td>0.145</td>
</tr>
<tr>
<td><strong>Human capital</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>yes = 1</td>
<td>-0.124**</td>
<td>0.058</td>
<td>-0.139***</td>
<td>0.058</td>
</tr>
<tr>
<td>Experience</td>
<td>log</td>
<td>0.027</td>
<td>0.051</td>
<td>0.038</td>
<td>0.051</td>
</tr>
<tr>
<td><strong>Social capital</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indegree centrality</td>
<td>log</td>
<td>0.043</td>
<td>0.029</td>
<td>0.197**</td>
<td>0.084</td>
</tr>
<tr>
<td>Indegree centrality²</td>
<td>log</td>
<td>-0.059*</td>
<td>0.030</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bridging ties</td>
<td>log</td>
<td>-0.219***</td>
<td>0.051</td>
<td>-0.225***</td>
<td>0.051</td>
</tr>
<tr>
<td><strong>Vessel specific variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vessel age</td>
<td>level</td>
<td>-0.009***</td>
<td>0.003</td>
<td>-0.009***</td>
<td>0.003</td>
</tr>
<tr>
<td>Vessel size: small</td>
<td>yes = 1</td>
<td>0.219**</td>
<td>0.102</td>
<td>0.212**</td>
<td>0.101</td>
</tr>
<tr>
<td>Vessel size: medium</td>
<td>yes = 1</td>
<td>0.242***</td>
<td>0.058</td>
<td>0.235***</td>
<td>0.058</td>
</tr>
<tr>
<td><strong>Owner specific variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Owner-operated</td>
<td>yes = 1</td>
<td>0.073</td>
<td>0.054</td>
<td>0.066</td>
<td>0.054</td>
</tr>
<tr>
<td>Ethnicity: E-A</td>
<td>yes = 1</td>
<td>0.280***</td>
<td>0.066</td>
<td>0.240***</td>
<td>0.069</td>
</tr>
<tr>
<td>Ethnicity: K-A</td>
<td>yes = 1</td>
<td>-0.122</td>
<td>0.079</td>
<td>-0.163**</td>
<td>0.082</td>
</tr>
<tr>
<td>Constant</td>
<td>level</td>
<td>-11.590***</td>
<td>1.830</td>
<td>-11.619***</td>
<td>1.828</td>
</tr>
<tr>
<td>$R^2$</td>
<td></td>
<td>0.404</td>
<td></td>
<td>0.407</td>
<td></td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td></td>
<td>0.394</td>
<td></td>
<td>0.396</td>
<td></td>
</tr>
</tbody>
</table>

*, **, *** denotes significance at the 0.10, 0.50, and 0.01 level.

5.6 Discussion

5.6.1 The Role of Social Capital

This research documents the strong relationship that social capital has on the performance of commercial fishers, and indicate that different dimensions of social capital and the context in which they operate need to be distinguished. In line with recent research in fisheries (Mueller et al. 2008, Turner et al. 2014), we found network prominence to raise the productivity of both
vessel owners and captains (Tables 5.4 and 5.5). These results support widespread (but largely untested) claims of the value of information in fisheries (Mangel and Clark 1983, Rudd 2001, Salas and Gaertner 2004, Dreyfus-Leon and Gaertner 2006, Gezelius 2007), and support recent propositions that structural social capital likely plays a significant role on fisher productivity (Barnes-Mauthe et al. 2014). However, for vessel captains operating at the trip level, we found strong evidence of decreasing returns to centrality (Table 5), suggesting there is an optimal level of connectedness, beyond which the costs of adding additional ties outweigh the benefits. Considering the dynamic and complex environment in which vessel captains operate and the short time frame in which they need to make decisions, it is reasonable to assume being overly connected is indeed likely to result in information overload as they are faced with larger inflows of information and the cognitive pressures of processing it (Schneider 1987, Ferriani et al. 2009). Though the vast majority of research on social capital and performance has emphasized a positive, linear association, evidence of diminishing marginal returns of various dimensions of embeddedness have been rapidly emerging, suggesting a nonlinear relationship may be more pervasive than originally assumed (Aral and Van Alstyne 2007, Ferriani et al. 2009, Molina-Morales and Martínez-Fernández 2009), particularly in complex environments.

Though we also found indegree centrality raised the productivity of vessel owners at the annual level, we found no evidence of diminishing returns to centrality in this case (Table 4). Vessel owners making long-term decisions that may affect annual productivity, such as hiring of captain or crew or innovating by upgrading vessel technology, reasonably have much more time to process information they receive from others than vessel captains making decisions at the trip-level, which may help to explain this difference. This result is provocative because although a direct positive association between social interaction and performance and innovation has been documented (e.g., Tsai and Ghoshal 1998), we know of no other studies that have jointly examined this relationship in relation to short-term and long-term performance in the same setting. Our results therefore suggest that the temporal scale at which the effect of network prominence operates mediates its role on productivity in an important way, and is certainly worthy of future study.

Among both owners at the annual level and captains at the trip-level our hypothesis regarding brokerage was supported: bridging ethnic groups significantly reduced productivity. In line with identity theory and role conflict, we argue that in this case brokerage decreases productivity due to a lack of trust across socially distinct ethnic groups and a general suspicion of those
interacting across ethnic divides. More specifically, we suspect brokers are being penalized for interacting with other groups, where the penalty consists of a general withholding of important information that may increase their efficiency. In conducting fieldwork, a general mistrust of other ethnic groups and brokers that span these groups has indeed been observed. Adverse effects of ethnic fragmentation on cooperation, trust, and the provision of public goods have been supported empirically by a number of recent studies (Alesina and La Ferrara 2002, Pomeroy et al. 2007, Chakravarty and Fonseca 2014, Alesina et al. 2014), and previous research does suggest that network relationships not only facilitate but can also hinder the behavior of individuals due to peer pressure and normative expectations (Krackhardt 1999). Where groups have strong social identities, it has been argued that brokerage is not likely to generate benefits (Podolny and Baron 1997). Our results show that not only is this the case, but under conditions of strong ethnic homophily in a competitive environment, brokerage across ethnic divides has a significantly negative relationship with productivity.

Our results support an emerging, more comprehensive theory of brokerage that recognizes its potential perils and the importance of context (Stovel et al. 2011, Stovel and Shaw 2012). The dark side of brokerage was recently highlighted by Bizzi (2013), who demonstrated that group composition can exercise a constraining effect on individuals, which can negatively impact performance. Arguing that the structural hole thesis may be culturally biased, Xiao and Tsui (2007) have also provided evidence that the benefits of brokerage typically manifested in individualistic cultures can have negative effects in cultures where working collectively is considered important. Aral et al. (2011) further demonstrate that brokering between disparate parts of a social network can result in disadvantaged access to information, particularly in turbid and high-dimensional environments. Recent work by others also support the notion the brokerage is a fragile relation, and its potential for generating benefits are highly context dependent (Ahuja 2000, Lazega 2001, Reagans and Zuckerman 2008).

5.6.2 Other Factors Influencing Productivity

The strength of the social capital variables stand in sharp contrast with the less robust and partially counterintuitive results regarding human capital, a result similar to that found by Fafchamps and Minten (2002). This does not imply that human capital is unimportant, particularly in the case of vessel owners. Rather, it does suggest that social capital is more important in this case, especially for vessel captains, where experience plays an insignificant
role and education is actually negatively associated with productivity. Though we lack qualitative data that may help to explain this result, it is certainly worthy of future study.

In line with previous analysis of economic productivity in HLF, vessels that target swordfish tend to be less efficient than those that target tuna only (Sharma and Leung 1999). Compared to previous inquires where over 20% of vessels targeted swordfish only and only 10% switched from swordfish to tuna during the year (Sharma and Leung 1999), we found that only 15% of vessels targeted swordfish, all of which switched to tuna during some portion of the year (Table 5.2). In addition to there being a greater return on tuna fishing, a number of strict regulations have been imposed on the swordfish fleet over the past decade intended to protect vulnerable and endangered sea turtles, which combined likely help to explain this changing dynamic. We also found vessel age to have a significantly negative effect on productivity, likely due to depreciation. Our results also show that operating smaller or medium sized vessels generate greater returns than operating larger vessels, particularly for trip-level revenue (Table 5.5). Though this is in stark contrast to previous research, which suggested Hawaii's longline fishers operate larger vessels in order to increase productivity (Sharma and Leung 1999), the cost of fuel has exponentially increased since then, and larger vessels typically require more fuel than smaller and medium sized vessels to travel the same distance (Kalberg and Pan 2014).

Interestingly, in contrast to earlier examinations of the factors that influence productivity in HLF (Sharma and Leung 1999), we found that owners operating their vessels are significantly less efficient at producing annual revenue (Table 5.4). This particular fishery is unique in that it operates year round, with vessels often only spending a few days in port between fishing trips. Thus, it may be that the time and effort spent on tasks and decision-making related to fishing trips detracts from the time and energy vessel owners would otherwise have to spend on long-run decision making, such as upgrading vessel technology and finding a more efficient crew. In this case, a delineation of responsibilities between two people making short-run and long-run decisions may actually benefit overall vessel productivity. The number of owners who also operate their vessel has indeed substantially declined. Specifically, Sharma and Leung (1999) report that 56% of vessels were owner-operated in 1993, whereas less than 35% were in our analysis. Though the reason for the decline in owner-operated vessels between the two time periods is unclear, it is possible that vessel owners have observed a benefit from dividing up the tasks and responsibilities associated with short-run and long-run decision making, particularly if they can find a good, reliable captain.
Finally, our results indicate that there are clear differences in productivity across ethnic groups. At both the trip and annual level, E-A fishers appear to be performing better than others, while K-A fishers are significantly less productive at the trip level (Table 5.5, model 2). This effect was previously predicted by Barnes-Mauthe et al. (2013, 2014) in two interrelated inquires that highlighted similar disparities in social capital resources among K-A fishers. Though there have been several economic studies on HLF (Sharma and Leung 1999, Pradhan et al. 2003), ethnic affiliation among actors has not been previously considered as a potential explanatory variable in explaining productivity. Yet our results show clear economic disparities across ethnic groups, which can be augmented by fisheries policies and impact long-term economic sustainability.

5.6.3 Limitations

The results of our analysis are qualified by some limitations, particularly related to endogeneity and reverse causality in our research design. The possibility for endogeneity arises because productive fishers are likely to have idiosyncratic features, such as abilities, expertise, and experience, that differentiate them from others, which may potentially also explain their position in the overall network structure. In this context, other fishers may seek out these individuals to gain access to their skills and knowledge, thereby increasing their prominence in the network. Though we acknowledge the possibility of a simultaneity bias, or reverse causation, we believe the threat of endogeneity in our empirical models is likely to be minimal. First, the models include several individual-level covariates that have been found to be important for explaining network position and brokerage and differences in productivity (including experience, education, and simultaneously owning and operating a vessel) in this particular fishery (Pradhan et al. 2003, Barnes-Mauthe et al. 2014). Although there is still the possibility of omitted variable bias, we believe these variables control for much of the unobserved heterogeneity in individual ability to generate greater returns, and the social capital variables remain statistically significant and far exceed the effects of the individual-level controls.

In addition, reverse causality was partially dealt with in the manner in which we designed our initial social network survey. Rather than using second-hand data on individual associations, we specifically asked fishers to identify relationships they felt were important for fishing success. Still, we acknowledge the risk of endogeneity, and suggest future research leverage dynamic network data to control for network formation processes and exploit lagged outcomes to more resolutely establish causality. In spite of these limitations, our study is important because it
provides evidence of the dark side of social capital and the role of competing social identities in overturning the classically positive effects of brokerage. By leveraging several unique sets of data in an ethnically diverse CPR system, we contribute to a more comprehensive theory of social capital and economic outcomes.

5.7 Concluding Remarks

By their very nature, social relationships constitute information channels that can reduce the amount of time and investment necessary to gather and process information, and can facilitate learning and the diffusion of innovations. The value of being well-connected or spanning diverse groups in networks is that it provides increased opportunities to capitalize on these benefits. However, our research shows that the ability to realize the benefits of network prominence and brokerage are highly dependent on context. To date, the overwhelming majority of empirical evidence linking social capital to explicit economic advantage stems from largely homogenous populations in management and corporate settings in Western settings. Here, we extended this work to account for an ethnically diverse population competing over limited CPRs. Our results provide novel evidence that in cases where social identities are strong and divides between groups pronounced, brokers are significantly less productive, which we argue is due to a lack of trust across groups and a penalty others place on brokers for bridging distinct social divides. Our findings also provide support to an emerging theory of nonlinear returns to network prominence by showing that temporal context matters. When actors need to make quick decisions in highly dynamic and uncertain environments, there are diminishing returns associated with being overly connected.
References


Barnes, M., K. Kalberg, M. Pan, and P. Leung. When is brokerage negatively associated with economic productivity? Ethnic diversity, competition, and common-pool resources. Social Networks (in review).


Pan, M., H. Chan, and K. Kalberg. 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, USA.


Rudd, M. A. 2001. Accounting for the Impacts of Fisher's Knowledge and Norms on Economic Efficiency. UBC Fisheries Centre Research Reports.


