The Effect of Fishery Management on Information Sharing Networks and Social Capital

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Abstract: The benefits from increased levels of social capital have been shown to manifest themselves in ways that can increase the efficiency of the use and regulation of natural resources, as well as increase the resiliency of resource dependent communities against fluctuations in abundance. While the literature shows ample evidence of the positive effects that social capital can have on management and stakeholder institutions, few studies examine the effects of changes in management on levels of social capital in commercial fisheries. This study employs network and econometric analyses to examine social capital in the Northeast multispecies groundfish fishery. We compare alternative measurements of social capital, and find suggestive evidence of decreased levels of social capital associated with a recent change from effort-based to rights-based management. Increased knowledge of this relationship may provide tangible benefits to both management institutions and resource users.

Keywords: fisheries, groundfish, information sharing, networks, sector management, social capital

I Introduction

Social capital--the relationships between individuals and groups of individuals facilitated by trust, cooperation, and norms of reciprocity--is interconnected with how people manage natural resources (Bodin, Crona, 2006, 2009; Bouma, Bulte, Soest, 2008). Studies have found that increased levels of social capital provide benefits to resource users and management institutions through increasing efficiency and compliance among resources users, and through facilitating the flow of information between resource users, and between resources users and managers (Bodin, Crona 2006; Knack, Keefer, 1997). Social capital can provide these benefits by incentivizing behavior through trust, cooperation and social networks (Curtis, McConnell, 2004; Paldam, 2000).

Conversely, the way people manage natural resources and the institutions that govern resource management can also affect levels of social capital. Given the benefits that stem from social capital to resource management institutions and user institutions, this association between social capital and resource policy is of importance. Previous literature indicates such an association, and that resource management institutions may have the capacity to affect levels of social capital (e.g., Bouma, Bulte, Soest, 2008; Paldam 2009). Paldam demonstrates this concept with an example of a benevolent third party incentivizing trust in economic transactions. Further, Bouma, Bulte and Soest observe a relationship between social capital and collective action, but find that this relationship becomes ambiguous with the addition of government subsidies. Very little empirical evidence exists that examine the relationship in this direction between resource policy and social capital. Furthermore, there has been no application of this research in the context of commercial fisheries.

To address this gap in the literature, the overall goal of this paper is to empirically examine the association between a discrete change in fishery policy and changes in social capital among fishermen. To do so, we apply several alternative methods of measuring social capital.

We collect network data from fishermen in the Northeast groundfish fishery through a survey. Using this data we measure social capital through network size and density, and incorporate variables to measure the quality and frequency of network relationships. We use regression and network analysis to provide an empirical and visual description of the relationship between social capital and fishery management.

Results indicate a decrease in the level of social capital during the years surrounding the change in management. Among those individuals in our study, network size; as well as quality and frequency of relationships decreased with the corresponding change in management. We interpret these results and their potential role in future fishery management decisions.

Although this study deals specifically in the context of fishery resources, the concepts are applicable to other scenarios involving the relationship between institutions and social capital. The implications of this research are that resource management institutions may influence levels of social capital positively or negatively by incentivizing or disincentivizing behavior that fosters the development of social capital. Further, this research suggests that incorporating measurement of social capital into the evaluation of resource policy may allow policymakers to assess impacts from social perspectives.

The rest of this manuscript is organized as follows. Section II discusses the definition and measurement of social capital, and the relationship between social capital, networks, and fishery management. Section III describes the background of the fishery in our analysis and our associated hypothesis. Section IV discusses the methodology of this study and the results of our network analysis. Section V describes the results of our regression analysis, and in section VI we cover discussion points and concluding remarks.

II Social capital: Definition and Measurement

Social capital is a term with multiple definitions based on concepts of trust, cooperation, and networks. Several definitions contain all three components, describing social capital as a characteristic of communities in which trust, cooperation and networks facilitate collective action (Bouma et al. 2008). Other definitions place different emphasis on these attributes, defining social capital as "the connections among individuals… the social networks and the norms of reciprocity and trustworthiness that arise from them" (Putnam 2000). To employ a game theoretical definition, social capital can be thought of as a propensity to play the cooperative solution even if it is not the Nash equilibrium, i.e., cooperation exists where it normally would not. In political science terms, social capital can be related to the emergence of cooperation in the form of *esprit de corps*, or cooperative behavior formed in excess of the requirements of a formal institution, i.e., cooperation exists when it is not formally required (Paldam, 2000).

Common underlying themes of trust, cooperation and networks can be seen in one capacity or another throughout the definitions of social capital. These themes are the basis for measurement from which we can identify two separate strategies for quantifying this concept. The first strategy defines social capital in terms of trust and cooperation. Research on the role of trust in social interaction indicates that economic activities that require agents to rely on the future actions of others are accomplished at lower cost in higher trust environments. Returning to the game theoretical description, trust is believed to reflect the percentage of people in a society who expect that most others will act cooperatively in prisoner's dilemma contests (Knack, Keefer, 1997). In the classic form of the prisoner's dilemma, the Nash solution is realized when both players defect. However, given additional trust between players, there is a theoretical point where the cooperative solution is realized, yielding a higher payoff for each player. This process by which trust leads to cooperation is referred to as the trust-cooperation complex and illustrates the relationship between trust and social capital (Paldam 2000). The trust-cooperation complex shows that higher levels of trust will bring about more cooperation, indicating higher levels of social capital.

The second strategy to measure social capital utilizes the characteristics of networks among individuals and between groups of individuals. The rationale behind this strategy is that individuals form cooperative groups with others along established norms of trust and reciprocity, implying that greater network activity indicates higher levels of social capital. Examples of networks lie in various settings, which can be ordered by degrees of formality. A group of coworkers that meet every week at the local bar for happy hour constitutes an informal network, whereas a PTA or a labor union represent more formal networks (Putnam, 2000). In each of these settings we can observe levels of trust and cooperation associated with network involvement. Hereafter referred to as the *network proxy*, this method maintains that we can measure levels of social capital as the amount of networks an individual has built (Paldam, 2000).

A number of studies have examined the relationship between networks and social capital, with differences in how each study employs the network proxy. The most notable research on social capital using the network proxy is Putnam (2000). Putnam discussed how social capital can be measured through bonding (within network) and bridging (between networks) relationships between individuals and groups of individuals. Through the network proxy, Putnam observed involvement in voluntary organizations to measure levels of social capital in the US from 1968 to 1997. He discussed trends in civic engagement as useful measures to describe levels of social capital, and illustrated that participation in voluntary organizations decreased during the study period. In a study that analyzed the link between social capital and value creation, Tsai and Goshel (1998) used a survey instrument to study intra-firm networks. Their method distinguished between formal business networks and social networks, finding that social capital facilitates value creation within firms.

Several studies have also used the network proxy to study the relationship between social capital and the use of natural resources. For example, research on the role of network structures in natural resource governance by Bodin and Crona (2008) analyzed networks based on occupation separate from those based on reported relationships. They concluded that "social processes which underpin the outcomes of resource governance are enhanced or inhibited by different [network] structures". Similarly, Ramirez-Sanchez and Pinkerton (2009) employed the network proxy in their study of social capital among fishermen in Loreto, BCS, Mexico. Through a survey instrument researchers gathered information regarding various characteristics of respondents' networks, and used network analysis to study the relationship between social capital and resource scarcity. They concluded that social networks within and between communities are activated according to changes in resource abundance. It is worthwhile to note that this study also measured levels of social capital as being influenced by another factor, in this case; resource scarcity. In contrast to studies which examined the effect of social capital on natural resource use, Ramirez-Sanchez and Pinkerton (2009) is the only work the authors are aware of that examined the reverse relationship, i.e., how the natural resource abundance affected social capital. While our research also examines social capital in this direction, we focus on the relationship between social capital and a change in management as opposed to fluctuations in resource abundance. Furthermore, we employ econometric analysis in addition to network analysis to provide empirical insight into our results.

In this manuscript, we employ the *network proxy* to assess the effect of a discrete change in fishery management on levels of social capital among fishermen. By examining multiple aspects of social capital as dependent variables, we attempt to provide a rich description of the association between the change in fishery management and levels of social capital. Through this method we will be able to answer the question posed in the outset: Is there a relationship between a change in fishery policy and levels of social capital? Before approaching this question empirically, we examine endogeneity in the relationship between social capital and natural resource management institutions.

Social capital, networks, and information sharing in fisheries

"The utility of jointly produced information is greater than what could be produced were each to act independently"-John Gatewood, 1984

This quote illustrates the incentives that cause fishermen to form networks, and is the basis for discussion on the relationship between fishery policy and social capital among fishermen. Fishermen build social capital through the formation of networks to accomplish a variety of goals from increasing safety to affecting catchability. Further, research has shown that fishers' livelihood may depend on social capital that supports adaptive responses to resource fluctuation, external shocks, and other uncertainties (Ramirez-Sanchez, Pinkerton, 2009).

The formation of networks for the purpose of affecting profit can be seen in many fisheries. In the Bristol Bay salmon fishery, fishermen form selective “radio groups”, where groups of privileged fishermen use “scrambled” radios to relay secretive information to one another regarding productive fishing areas. These radio groups are highly exclusive and there are strict norms regarding information exchange outside of the group. Similarly, fishermen in the Southeast Alaska salmon seine fishery exchange information through networks of trusted fishermen regarding the movement of fish, vessel concentration, and other aspects of the industry that effect catchability (Gatewood, 1984). Fishermen share information about fish to increase their knowledge about the stock, and the likelihood that they will catch fish; decreasing the inherent risk in the industry. These information sharing networks have been shown to provide benefits beyond affecting profits, however; as networks are a common denominator in cases where different stakeholders have come together to effectively deal with natural resource problems and dilemmas (Bodin, Crona, 2008).

Networks formed for the purpose of sharing fishing related information differ than those formed for other reasons in that there exists an underlying cost and benefit structure. This structure is influenced by the nature of the fishery and may affect how much information (if any) is exchanged between the two individuals. To fully examine why there may be costs to sharing information about fish requires a discussion of several distinct attributes commonly used to describe natural resources: rivalry and congestion. Fishery resources are rivalrous in that the harvest of fish by one cannot be proceeded by the harvest of the same fish by another. This is an important concept in the context of information sharing in fisheries because it implies a certain amount of loss or forfeiture of profit by the individual divulging the information. Since fish are mobile and largely unobservable, there is no way to know how much fish a fisher may be “giving up” by sharing information. Lastly, by sharing information regarding a favored fishing location, fishermen impose a congestion externality on themselves. Through multiple fishermen trying to occupy the same area simultaneously, some individuals are inevitably “crowded out” of optimal fishing areas, causing a loss in revenue. Through these features of the fishery resource, it can be seen that the costs to sharing information may affect the formation of networks in which fishermen share information with one another. Given that we can measure social capital through networks formed on the basis of information sharing, it stands to reason that the formation and maintenance of these networks may be linked to changes in fishery policy.

Fishery policy and networks

Fishery policy may affect levels social capital by changing the rules surrounding the use of the resource. By changing the rules, fishery managers may alter the economic incentives associated with forming networks. When a network of individuals is confronted with a new economic opportunity, members will wish to re-negotiate their relationships (Dasgupta 2005). Consider the following example of a fishery that undergoes a transition in management from an effort based management system to an output based management system (e.g., limited entry and quota management, respectively). In this fishery, suppose that several fishermen come together and form a network whereby each fisherman shares information with the others. This fictitious network is bound by 4 assumptions: First, by participating in this network each fisherman is made better off through increased knowledge, which reduces the risk of an unprofitable fishing trip. Second, by the concepts of congestion and rivalry discussed earlier; each additional fisherman is also a potential competitor. Third, by sharing information each fisherman may consider with some certainty that the other will adjust his behavior accordingly. Finally, the exchange of information is bound by norms of reciprocity, i.e., each fisherman is obliged to reciprocate information if they want the relationship to be available in the future. In a nutshell, these fishermen participate in this network because it is advantageous for them to do so despite that sharing more information increases competition for fish. Further, they share information in both directions and assume that information provided will be used. Given these assumptions, we can discuss how the various costs and benefits of sharing information might affect network behavior among these individuals under an effort limiting management system. Under this system, there are a limited number of fishermen that must compete against one another for a portion of total catch.

Each fisherman has information that will affect the expected value of a fishing trip. Therefore we can express the benefit of sharing information as an increase in the expected value of a trip. Fisherman A would like to increase the expected value of his trip, so he shares information with fishermen B and C. However, if A shares information with additional fishermen he may encounter the same information. It can therefore be seen that the marginal benefit of sharing information with one more fisherman may decrease as the number of fishermen increases. Suppose a similar scenario to illustrate the costs associated with sharing information. Through sharing information with B and C, A has incurred upon himself a decrease in expected value by purposefully introducing additional congestion on his fishing area and rivalry for the fish. Through our first assumption however, we know that A has considered this and is still better off than he would be had he not shared his information (e.g., he may think there is more than enough fish and space for both himself and others to exploit). As the other fishermen have the same incentives, it can be seen that each will share a respective level of information that will reflect their perceived marginal benefit and cost of information.

Now suppose the same fishery undergoes a change in management whereby a total allowable catch (TAC) is established and each fisherman is restricted to a percentage of this TAC. Under the new management system, fishermen A, B and C all have a specific amount of fish that they are allowed to catch. If we apply the previous scenario, we can illustrate changes in both the cost and benefit of sharing information. Consider A's decision on whether or not to share information with B. Remember that both are bound by the norms of reciprocity, and assume that A has not yet shared information with anyone else. A's cost of sharing information with B has changed because he knows that B can only catch a certain amount of fish. Given that both fishermen can no longer catch as much fish as they want, A does not have to worry about B catching all of the fish, just some of them. Because of this reduction in competition, each fisherman can worry less about catching as much fish as possible and more about catching fish as cheaply as possible. This leads us to the benefit side of the argument. Because incentives now exist for each fisherman to decrease the cost of fishing, there may be a greater benefit in knowing where the fish are. We can therefore see that in this simplified example the alteration of perceived costs and benefits may affect how these fishermen share information. This simple scenario illustrates how a change in fishery policy may affect social capital by influencing the rules of harvest, therefore affecting the costs and benefits of sharing information through networks. Given this relationship, we apply similar intuition to examine how a change in management may affect networks among fishermen in the Northeast multispecies groundfish fishery.

III Northeast Groundfish Fishery Management and Hypothesis

We test our hypothesis in the context of the Northeast multispecies groundfish fishery in Stellwagen Bank, Massachusetts. This study is part of a larger project to assess the effects of fishing area closures in the Stellwagen Bank National Marine Sanctuary (SBNMS) on groundfish fishermen and their communities. This setting creates a unique opportunity to examine the association between fishery management and social capital because the industry recently went through a discrete and significant change in fishery management which may have changed the incentives of fishermen to share information. This section provides a brief overview of the groundfish fishery and its recent transition in fishery management.

The Northeast multi-species groundfish fishery is one of the oldest fisheries in the US. Colonial settlers used hooks and lines to catch fish, leading to the eventual establishment of historical ports such as Gloucester and New Bedford (Gordon 2010). The groundfish fishery developed into one of the largest and most valuable in the country; drawing international attention and leading to exploitation in domestic waters by large foreign vessels. In 1976 the US Congress passed the Magnuson-Stevens Fishery Conservation and Management Act (MSFCMA), which established an exclusive economic zone to 200 nautical miles from the coast. The MSFCMA effectively forced out foreign vessels and facilitated a rapid increase in domestic fishing capacity. The resulting over-capacity of the domestic fishing fleet is credited with the eventual collapse of several groundfish species in the 1980's. In response, the New England Fisheries Management Council instituted a series of effort-limiting management measures, which culminated in the Days-At-Sea (DAS) system. In place until May, 2010; the DAS system limited fishing effort by assigning each vessel a specific number days they were allowed to engage in commercial harvesting. Under this system fishermen were forced to compete against one another for a share of an annual catch target defined by the regulator. This management system created incentives resulting in several negative externalities typically associated with effort based management; including capital stuffing and the propensity to engage in risky behavior.

In response to the inability of the DAS management system to appropriately address conservation issues, the New England Fisheries Management Council developed an amendment to the Northeast groundfish fishery management plan. Amendment 16 introduced sector management into the fishery in May 2010.

Sector management is a variation of fishery management commonly referred to as rights-based management. In general, under rights-based management; fishermen have a claim to harvest an excludable and predetermined quantity of fish. In contrast to the incentive to "race to fish" created by the DAS system, rights-based management assigns each fisherman a quantity of fish that they are allowed to harvest; if one fisherman chooses not to fish the other fishermen could still only catch their allowed amount. Sector management is one type of rights-based management, where fishermen are divided into groups and assigned quota to be distributed amongst them however they see fit. In New England, annual allocations are assigned to each sector. Individual fishermen within sectors then decide how to distribute the sector allocation. The majority of sectors divide the allocation based on historical harvest, effectively creating individual quota for each member. The quota is transferable within and (with some restrictions) across sectors. Through the use of individual quota, the sector management system incentivizes fishermen to maximize profit instead of revenue. Further, managing quota at the sector level increases the relative flexibility stemming from the use of localized management, knowledge, and expertise (Holland, Silva, Wiersma, 2010).

Studies have found that the transition between management systems based on effort limitation to rights-based management can alter fishermen's behavior. This change in behavior often originates due to a shift from revenue maximizing to profit maximizing behavior (Knapp, Murphy, 2010). This study utilizes the discrete change in the Northeast groundfish fishery from DAS to sector management to examine the effect on social capital among the groundfish fishermen through the change in information sharing behavior.

Hypothesis

Capitalizing on the discrete change in the groundfish fishery management in New England, we seek to understand how fishery management affects information-sharing networks. Based on the conceptual discussions in the previous section, the total effect of the change from DAS to sector management is ambiguous. Positive effects of the change in management on social capital may stem from a reduction in the cost of sharing information, thereby increasing communication between fishermen and increasing social capital. Conversely, negative effects would increase the cost of sharing information and thus decrease social capital. As we cannot directly observe changes in the incentives regarding network formation, we infer this effect through our measures of social capital. We therefore hypothesize that the discrete change in management in the Northeast multispecies groundfish fishery is associated with an observable change in social capital. We also hypothesize that this association may be heterogeneous across sectors. We test these hypotheses using network and regression analysis.

IV Network analysis: Methodology and results

We use survey data to test the association between fishery management and social capital. We use qualitative and quantitative methods to analyze the data. Using network analysis, we illustrate the visual differences in network characteristics between the years surrounding the change to sector management. We then use regression analysis to empirically illustrate this scenario, treating our selected measures of social capital as dependent variables. The use of both methods of analysis allows qualitative and quantitative examination of our hypothesis.

Data

The primary data for this study were obtained from a survey administered as part of a larger project to assess the effects of fishing area closures in the SBNMS on groundfish fishermen and their communities. The survey was developed over three months in 2010 with the aide of an in-sample focus group and then pretested to an out-of-sample group of 6 fishermen. Following several revisions, the survey was administered during 2011 in 3 fishing communities of

Gloucester, Duxbury, and Scituate Massachusetts. Survey sessions were organized in advance and held at predetermined locations, where surveys were administered using either paper or electronic media. The survey took an average of 1 hour to complete, and respondents were compensated $100 for their time. We administered a total of 69 surveys, with a valid response rate of approximately 80%.

This study utilizes several sections from the survey related to individual fishing behavior, business decisions, network relationships, and demographics. In most of the sections we use in this survey, we asked for information for 2009 (before sector) 2010 (after sector). Hence, the before-sector data is recall data. The network variables we construct in this study come from a section of the survey consisting of 24 questions regarding fishermen's networks and fishing related information sharing behavior. We asked the respondents with whom they share general and specific fishing-related information. During the focus group, specific information was identified as having a sensitive or private nature, which a fisherman would typically only share within a limited group of 4-6 individuals. Accordingly, the survey asked the respondents to list the names of up to 5 individuals with whom they shared specific fishing related information. For each named individual, respondents were asked how long they had known each individual, what they had in common with that person, and whether or not they were related. These were followed by several questions regarding the type, level of detail, and frequency of information shared with each listed individual. We asked the respondent to identify the type(s) of information (out of 8 identified in the focus group) they discussed with each individual. We also asked the respondents to rate the level of detail of which they shared information using a Likert scale from 1 to 8 (1 = low, 8 = high) for each listed individual. In addition, we also asked how often they shared information with each individual. As previously mentioned, to capture changes between 2009 and 2010 fishermen were asked to answer the exact same set of questions for both years, with an additional question for 2010 inquiring whether a listed individual was also in the same sector as the respondent. We asked similar questions regarding the degree to which the respondents shared general fishing related information (see Appendix A for an example of survey questions).

Using data from the survey questions, we construct several variables to describe respondents' information sharing network, their relative position within the network, and various personal attributes. Additional data on sector and permit membership was retrieved from National Marine Fisheries Service (NMFS, 2012). This data indicates the permit, respective sector number, and eligibility date range for respondents in our survey data set. By combining the sector information with our survey data we were able to perform further analysis of respondents' information sharing behavior based on sector membership. We then applied these variables in network and statistical analysis to test the hypothesized relationship between fishermen's networks and the discrete change in management from 2009 to 2010.

A limitation of this study stems from the fact that all of the groundfish fishermen in our sample are participating in the sector program. Hence, we do not have a convincing control group. The implication is that in testing the effect of sector management on fishermen's networks, we are forced to resort to their pre-sector behavior (2009) as the counterfactual. Accordingly, we interpret the association between the new fisheries management and the changes in networks (social capital) as an association, not causality.

Network analysis

We use survey data on networks to analyze the differences in respondents' networks between 2009 and 2010. The data set is analyzed in NodeXL, an open source network analysis software which allows graphic illustration of each respondent's network as well as the calculation of several network- related statistics. In the analysis, individuals and their relationships are indicated as nodes and links, respectively. A node is an actor in a network. In our data, a node can be either a respondent or a member of a respondent's network. Links are the relationships between the nodes in a network and represent information sharing relationships between fishermen.

We first illustrate the networks graphically (Figures 1, 2). In these figures, we weight the thickness of links in the graph to reflect the frequency of communication between the fishermen. Additionally, we adjust the appearance of the links to show reciprocity of information: a solid link indicates a relationship in two directions, while a dashed link indicates an information sharing relationship in one direction[1]. To illustrate the differences among individuals in the network, the size of nodes reflect the number of links connected (degree), and the shade of the nodes reflect relative importance (PageRank) within the network (dark = more important, light = less important). Lastly, by virtue of the graph layout, the distance between nodes reflects the level of detail of information shared between individuals, i.e.; individuals that share a higher level of detail of information are positioned more closely together.[2]

Using the data, we calculate two variables to characterize each respondent's networks:

1) *Degree:* The degree is the number of links that connect each node. Degree is the number of either incoming or outgoing links, indicating the direction of the relationship between

individuals. The total number of degrees within a network helps to define the density of the network, i.e., a network with a higher degree is more dense than one with a lower degree.

2) *Centrality:* Centrality is a measure of importance within a network. In this study we use the PageRank measure of centrality. PageRank calculates the relative influence of a particular node on the flow of information within its network, weighted by the influence of the nodes connected to, i.e., a node is more influential if the nodes it is linked with are also influential.

Results of network analysis

We find that between 2009 and 2010, the overall network size decreased (see Figures 1 and 2 for network graphs and Table 1 for statistics on network variables). The decrease in overall network size can be observed by the decline in the number of nodes, and a corresponding decrease in the number of links. We also find that that the overall importance of nodes (as indicated by PageRank) within the network has decreased. This result is seen by examining the shade (which indicates its importance in the network) and size (which indicates the number of connected links) of the nodes. Comparing 2009 and 2010, we see that there are fewer large, darker shaded nodes in 2010. This is intuitive because the influence of an individual in a network will depend in part on the number of relationships they have with others, which is influenced by overall network size. In addition, we find that the number of smaller, lightly shaded nodes has decreased in greater proportion to the larger, darker shaded nodes. Finally, recall also that the distance between nodes is weighted by the level of detail of information shared between individuals. In addition to there being fewer of them, we also observe that the nodes are very slightly further apart. However this observation may be due to the smaller network size and its effect on the layout of the graph.

In contrast, we find that there is a slight increase in network density between 2009 and 2010, caused by a comparatively larger decrease in the number of nodes over the number of links. Similarly, we observe an increase in the average width of links in 2010, indicating a relative increase in the frequency of information shared. Also, we can see that there is a roughly proportional change in light versus dark shaded links, which is intuitive due to the aforementioned assumption of reciprocity.

These observations from visual inspection of the network graphics are confirmed by descriptive statistics. In Table 1, we see a decrease in the mean values of our network variables between 2009 and 2010; with the exception of network density. The increase in network density is intuitive when compared to the visual analysis in Figures 1 and 2, and indicates that the less important individuals within the network in 2009 did not participate in 2010.This argument is supported by the increase in relative frequency of information shared between individuals in 2010, and that the number of lightly shaded nodes has decreased in greater proportion to the larger, darker shaded nodes. In sum, we find that the overall network size decreased, but the remaining relationships within the network in 2010 may consist of individuals that respondents deem more important.

V Econometric analysis: Methodology and results

In this section, we use network variables in an econometrics framework to quantify the effect of the shift from DAS to sector management on information-sharing networks. The descriptive statistics of all variables used in regressions are provided in Table 2.

Dependent variables

One limitation in the literature on the measurement of social capital using the network proxy is that most studies measure networks using only one or two descriptive elements. To address this limitation, we describe networks in several dimensions: physical attributes given by network size and density, the type and level of detail of information exchanged between individuals, and the frequency of information exchange.

First, we measure social capital through physical network characteristics, i.e., network density and network size (e.g., Paldam 2000, Holland et al. 2010). We specify *Network Density* as the number of existing relationships divided by the number of possible relationships. *Network Size* is represented by the number of individuals each respondent recorded in the survey.

In addition to physical network attributes, indices were created using information type, level of detail, and frequency variables. *Type Index* represents the types of information shared between individuals and was calculated as the standardized sum of the individual occurrences of a respondent sharing each type of information. These standardized values were then summed across all types of information to reflect the aggregate amount of information shared by each respondent. Variables describing level of detail and frequency of information shared were combined to produce *Frequency & Detail Index* used to describe the nature of quality of respondents' networks. This index represents the average of the standardized sums of the detail and frequency variables.

The resulting set of dependent variables reflects the physical attributes of each network, as well as the total amount and quality of information shared. We incorporate these variables to observe fishermen's networks in several dimensions, thus increasing the descriptive capacity of our network proxy.

Explanatory variables

We specify several explanatory variables to explain differences in networks between individuals. *Year* is our primary variable of interest, as it represents the effect of the change in management between 2009 and 2010. To capture the effects of income and effort, we specify a variable for fishing *efficiency*. This is justified, as literature (e.g., Putnam 2000, Knack & Keefer 1997) suggests that income is correlated with social capital. We account for effort based on intuition that more time spent fishing leads to greater accumulation of information and exposure to networks. We specify a *region* dummy to account for differences between communities that may affect network behavior. Lastly, we include a variable for *education* to capture effects on differences in human capital.

Regression model

We apply individual fixed effects in a seemingly-unrelated-regression (SUR). We include individual fixed effects because there may be systematic differences among respondents that may account for variation in their networks. For example, characteristics such as personality and personal experiences are unobservable and may have effects on network behavior. As such, without controlling for these variables our model suffers from omitted variable bias.

Additionally, we face the multiple inference problem in that we have four dependent variables to explain social capital. By regressing these variables independently, we ignore that there may be correlations between the error terms of each model. It is intuitive to assume that there are correlations by virtue of the fact that all dependent variables contribute to the explanation of one concept (Anderson, 2008). We therefore use SUR to allow correlation among the error terms between models. Combined, we estimate the following reduced model:

$$\textit{Social Capital}_{im} = \beta_{0im} + \textit{Year}_i\beta_{1m} + \textit{Efficiency}_i\beta_{2m} + \textit{Region}_i\beta_{3m} + \textit{Education}_i\beta_{4m} + \textit{FE}_i\alpha_{im} + \mu_{im}$$

where *m* represents model *m* for each dependent variable *(Frequency & Detail Index, Type Index, Network Density and Network Size)*. Individual fixed effects are represented as α_{im} where *i* represents each respondent, μ_{im} is our error term, and *year* is our primary explanatory variable of interest.

Results

Overall, our results suggest that there is an association between the change in fishery management and the change in social capital (Tables 3, 4 and 5). Coefficients on the *year* variable are significant and negative for regressions on *Frequency & Detail Index, Type Index*, and *Network Size*. This result indicates a decrease in overall network activity from 2009 to 2010 and a corresponding decline in social capital. We will now interpret these regressions individually.

We find that the change in fishery management is associated with a decline in *Frequency & Detail Index* (Table 3, Model 3). We find a negative and statistically significant coefficient on *year* (-0.817), indicating that respondents shared information less frequently and in less detail after the change in management. Given that the mean of *Frequency & Detail Index* in 2009 was 2.022 (Table 2), the results imply that on average the change in management is associated with a 40% decline in this index. This result concurs with the network graphs, which showed nodes placed further apart and fewer thick links within the network between the two years. Additionally, we find a positive and significant coefficient on the *year-region* interaction term, indicating that the quality of information shared between respondents from the Cape Ann region is higher than those from Cape Cod in 2010. Moreover, the R-squared values increased from 0.054 in the model without fixed effects (Model 2) to 0.773 in the model with individual fixed effects (Model 3). This difference indicates that the unobservable individual factors explain a significant amount of the variation in individual network behavior.

We also see a decrease in *Type Index* as indicated by the negative and significant coefficient on *year* (-1.170, Model 6). This result indicates that the change in fishery management is associated with respondents sharing less fishing-related information. Given that the mean of *Type Index* in 2009 is 2.542 (Table 2), the results imply that on average the change in management is associated with a 46% decline in this index. Also, we see a positive and significant coefficient on the *year-education* interaction term. This indicates that respondents with higher levels of education shared more types of information after the change in management than those with less education.

Taken together, the consistent, statistically significant and negative coefficients on the *year* variable in these regressions indicate that fishermen share fewer types of fishing information less frequently and in less detail after the change in management. From these results we can also observe that there are regional differences in respondents' network behavior, and that individuals with more education share more types of fishing information.

The regression results on the effect of fisheries management (*year*) on *Network Density* are positive but with weak statistical significance (Table 4, Models 1-3). Although the coefficients are positive and statistically significant in Models (1) and (2), the coefficient remains positive but becomes significant only at the 19% level when we include individual fixed effects in Model (3). This result illustrates that there are significant unobservable differences between individuals which explain the variation in *Network Density*. Given these results we limit our interpretation of the coefficient on *year* and simply acknowledge that the direction of sign concurs with the summary statistics and is qualitatively observable in the network graphs. Further, the fixed effects model shows a significant and positive effect on the *year-region* interaction term. This indicates that, in 2010; respondents from Cape Ann had more dense networks than those from Cape Cod. This result is also supported in our previous regressions.

Lastly, we find a negative and statistically significant coefficient on *year* in our regressions on *Network Size*, suggesting that the change in management is associated with a reduction in the size of respondents' networks (Table 4, models 4-6). Given that the average

Network Size in 2009 was .689, the point estimate suggests that the change in fisheries management is associated with a reduction in the *Network Size* by 55%. Further, we observe significant and positive effects on the *year-region* and *year-education* variables. This indicates that in 2010, respondents living in Cape Ann had larger networks than those in Cape Cod. Similarly, respondents with more education had larger networks in 2010 than those with less education. In summary, we can interpret these results as a decrease in *Network Size*, possibly caused by the absence of smaller, less important nodes.

Finally, we examine the direction and the magnitude of the total effect of the change in fishery management (*year*) and its statistical significance. In these hypothesis tests, the interaction term *education* is evaluated at its mean and *region* is set to Cape Ann (=1). We find that the total effect is negative and statistically significant for *Frequency & Detail Index* and *Type Index*, and positive and statistically significant for *Density* (Table 5). The total effect for *Network Size* is negative but provides weak statistical significance.

Using the mean value of *Frequency & Detail Index* (Table 2), results show that respondents from Cape Ann of average education shared information with 12% less detail and frequency after the change in management. This decrease persists in spite of a positive and statistically significant (1%) effect on *region* in our regression results (Table 3, model 3). This indicates that respondents from Cape Cod may experience an even greater decrease in *Frequency & Detail Index* associated with the change in management than those from Cape Ann. This is confirmed by adjusting our test specification (*region*=0), where we find a 35% decrease in *Frequency & Detail Index* associated with the change in management.

Evaluating the total effect of *year* on *Type Index*, we see that the same respondents share 14% fewer types of information after the change in management. Comparing this result with *Type Index* regressions (Table 3, model 6) we see that this decrease is significant despite a significant (10%) and positive effect on *education.* This result indicates that after the change in management, the number of types of information shared may have decreased further among less educated respondents.

Examining the total effect of *year* on *Network Density,* results indicate that respondents from Cape Ann of average education experienced a statistically significant (1%), 28% increase in *Network Density*. While the point estimate for *year* in our regression on *Network Density* (Table 4, model 3) was not statistically significant, we note the significant (5%) and positive effect of *region*. Given that our test specifies respondents from Cape Ann (=1), we can see that the additional effect of this interaction term increases the total effect of *year*. This indicates that while regression results on *Network Density* for respondents from Cape Cod were statistically ambiguous, those from Cape Ann may have experienced statistically significant increases in *network density* associated with the change in management. Evaluating our test again (*region=0*) confirms this and we see that significance decreases (10%) and that respondents from Cape Cod experienced an 11% increase in *Network Density.*

Lastly, the total effect on *year* indicates a 6% decrease in *Network Size*, but provides weak statistical significance (14%). Regression results (Table 4, model 6) show positive and statistically significant effects on *region* (1%) and *education* (5%). Considering our test assumptions, together these results indicate that respondents from Cape Ann with more education did not experience a significant decrease in *network size* associated with the change in management. Adjusting our test for those in Cape Cod however, we find a 34% decrease in *Network Size*, and significance increases (1%). This result indicates that *Network Size* was affected significantly more for respondents in Cape Cod.

Results from our tests of total effect on *year* indicate various effects of the change in management on our variables for social capital. We observe a statistically significant and negative total effect on *year* for *Frequency & Detail Index* and *Type Index*, and a positive and statistically significant on *year* for *Density* (Table 5). As specified, our test indicates a statistically ambiguous effect for *Network Size.* We interpret these results in conjunction with their respective regressions, and find that *region* and *education* may play a significant role in the effect of a change in management on social capital among our respondents.

Information sharing among sectors

Next, to further examine heterogeneity of information sharing across sectors, we test whether there are differences in social capital between sectors (e.g., whether fishermen in one sector inherently share information more or less than another), and whether the changes in the levels of social capital in association with introduction of sector management also vary across sectors. To answer these questions, we extend the previous empirical models by including sector information for each respondent. Specifically, we add sector fixed effects ($sector\_id_j$, taking on a value of 1 if the respondent is a member of sector *j* and 0 otherwise) and an interaction term between sector fixed effects and the year variable, which takes the value of 1 if post sector management. The dependent variables are the same as in the previous section.

The overall results indicate that there are differences between sectors, though those differences are largely not associated with the change to sector management (Table 6). The estimates of the sector fixed effects indicate that the average frequency and detail of information shared differs across sectors (model 1). Specifically, sectors 12, 13, and 15 shared information more frequently and in more detail compared to sector 2. Furthermore, among our respondents, the reported size of a respondent's information sharing networks is larger in sectors 12 and 15 (model 3). Similarly, we find respondents' membership in sectors 12 and 15 is significantly associated with the density of their information sharing networks (model 4). Lastly, we do not find evidence that these differences in information sharing networks are associated with the introduction of sector management, as indicated by the interaction terms between the sector fixed effects and the year dummy variable. The exception is that the size of respondents networks in sector 15 decreased after the introduction of sector management (model 3).

This analysis indicates the heterogeneous nature of social capital between sectors. Similarly, coefficients on the *region* variable in tables 3 and 4 and subsequent discussion suggest that individuals share information differently depending on geographic location. Taken together, the analysis of the *sector* and *region* variables suggest that respondents may share information differently depending on the pretense or institution under which they are organized.

VI Discussion

Results from our network and regression analyses indicate an association between the change to sector management and the level of social capital among fishermen in the Northeast multispecies groundfish fishery. We find that respondents' *Network Size* and *Network Density* have changed, and are influenced by heterogeneity in *education* and *region.* Network analysis results confirm this, indicating a decrease in the number of smaller, less important nodes and a relative increase in the number of links from 2009 to 2010. We observe statistically significant decreases in *Frequency & Detail Index* and *Type Index.* These results indicate that respondents shared information less often and in less detail after the change in management. This change in *Frequency & Detail Index* is reflected in the network analysis, which shows reduced presence of thicker links and nodes that are further apart. Overall, our results indicate a decrease in social capital and further suggest heterogeneity among respondents in the association between social capital and the change in management. Due to the limitations of our data, these results should be interpreted as an association, not causality.

In the introduction, we described a scenario in which fishermen acted in their best interests according to our assumptions. We described that fishermen form networks to increase their welfare, and within these networks they are bound by norms of reciprocity. We further assumed that fishermen believe the information they provide will be used, and they recognize that sharing more information increases competition for fish. Further study of these assumptions may provide additional insight and help reveal the mechanisms by which changes in resource management may affect network behavior.

In particular, we consider the assumption that sharing information increases competition for fish. This assumption illustrates the cost of sharing information through rivalry and congestion, and in this paper we employ a simplified scenario to discuss these costs as a direct association of a change in management. However, our analysis does not allow us to account for the possibility of an indirect association. To take this concept further, we question whether management changes have indirect effects on network behavior through markets.

In a follow-up focus group, we presented the preliminary results of this study to several fishermen who verified our findings. The following comment captured the groups' sentiment and provided some insight:

"Before sectors we all had scrambled radios in our boats and people were talking on them all the time. I can't remember the last time I used my radio. No one talks to each other anymore."

When asked why this was the case, fishermen said that if they tell others where the fish are the higher delivery volume will drive down the price. To test this theory, we ran simple regressions using data on fish prices and delivery volume for 2009 and 2010. When regressing the per-unit price of fish on daily delivered volume, we found a negative and significant coefficient on volume for both years. The result is intuitive and indicates that as the daily amount of fish delivered increases, the price decreases. On further analysis, however, we ran a log transformed model on the same data and found that the price elasticity of fish had indeed increased in 2010 compared to 2009. This informal analysis suggests that fishermen's network behavior may have been influenced through the market. Whether or not the change in management was a causal effect on this market scenario is unknown, but this illustrates that our analysis is limited by assuming only direct effects in the association between management changes and social capital.

Another interesting question arises when we consider the possible direct effects of sector management on social capital in the form of regulations or individuals that may directly encourage or inhibit information sharing between fishermen. One such possibility can be seen in the role of the sector manager. The sector manager is an individual who, by regulation; is appointed by the sector and whose position has three basic components: tracking and reporting the sector's landings, discards, and trades on a weekly basis; keeping track of the internal division of allocation and catch; and overseeing the trade of allocation with other sectors (Labaree, 2012). The question is whether in this capacity the sector manager may displace information that would have otherwise been exchanged between fishermen. However, given the role of the sector manager, the information displaced would likely be that which was necessitated by the sector itself, i.e., information regarding allocation and catch. We therefore reason that the impact of the sector manager on traditional subjects of fishing related information exchange is minimal. Further, questions in the survey were specified to address those areas of communication between fishermen that were unlikely to be directly affected by a change in regulation. To address this question empirically, we tested responses to a question regarding species composition that could be inferred through communication with the sector manager. Our results showed no statistically significant difference in the amount of information regarding species composition shared before versus after sector management. This implies that there either was no change in the amount of information shared regarding this particular subject, or the creation of the sector manager role offset the additional flow of information regarding species composition. Therefore, we maintain that the change in the amount of information shared between fishermen was not influenced by the sector manager.

VII Conclusions

Research has shown that social capital can lead to benefits for resource users and managing institutions. This study addresses the question of a reverse relationship between fishery policy and social capital among fishermen. To test this relationship we use network and regression analysis to identify differences in network characteristics before and after a discrete change in management. We use this methodology in conjunction with detailed survey information on fishermen's networks in the Northeast multispecies groundfish fishery and find a negative association between the change in management and levels of social capital. Our results indicate that there may be a dual relationship between social capital and resource policy, and that this relationship may be further influenced by heterogeneity in individual characteristics. This may carry important implications with regards to engineering resource policy that helps build social capital, allowing managers and stakeholders to take advantage of the benefits that come with it. Conversely, our results may serve as a caution for those attempting to utilize this association without information regarding the causal factors involved and the heterogeneity between affected individuals. To this end, more research is necessary to evaluate the direct and indirect effects of changes in resource policy and the ways in which various users are affected.

[1] While the previous section argues that information sharing is unlikely to occur without a reciprocal relationship, the nature of the data collection did not allow the full population of fishermen. This ensures that some edges will only reflect one-way relationships.

[2] We use a force-directed Fruchterman-Riengold layout algorithm.

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Table 1. Descriptive statistics for network analysis variables, 2009-2010

Variable	Year	n	Mean	Std. Dev.	Min	Max
Frequency	2009	69	2.734	1.393	0	5
	2010	69	2.277	1.636	0	5
Detail	2009	69	1.309	1.264	0	4.375
	2010	69	1.041	1.174	0	4.375
Type	2009	69	2.542	1.879	0	7
	2010	69	2.017	1.969	0	7
Density	2009	62	.002849	.001211	.000605	.006654
	2010	56	.003416	.001823	.000850	.009353
Network size	2009	69	.689	.365	0	1
	2010	69	.524	.398	0	1
PageRank	2009	62	1.383	.445	.395	2.414
	2010	56	1.328	.523	.384	2.632
Degree	2009	62	4.709	2.003	1	11
	2010	56	4.017	2.144	1	11

Table 2. Descriptive statistics for regression analysis variables

Dependent variables	Year	n	Mean	Std. Dev.	Min	Max
Frequency & detail index	2009	69	2.022	1.106	0	4.520
	2010	69	1.659	1.215		4.437
Type index	2009	69	2.542	1.879	0	7
	2010	69	2.017	1.969	0	7
Network size	2009	69	.689	.365	0	1
	2010	69	.524	.398	0	1
Density	2009	62	.002849	.001211	.000605	.006654
	2010	56	.003416	.001823	.000850	.009353
Explanatory variables						
Year	(time invariant)	128	.5	.501	0	1
Log of efficiency	2009	65	3.914	.972	2.002	6.124
	2010	65	3.773	1.043	1.087	6.118
Region	(time invariant)	128	.656	.476	0	1
Education	(time invariant)	124	2.387	1.025	1	5

Table 3. Regression results: Frequency & Detail, Information Type

VARIABLES	Frequency & Detail Index			Type Index		
	(1)	(2)	(3)	(4)	(5)	(6)
Year	-0.388*	-0.379*	-0.817***	-0.484	-0.516	-1.170***
	(0.208)	(0.205)	(0.311)	(0.344)	(0.332)	(0.341)
Log of Efficiency		0.0702	-0.119		-0.231	0.150
		(0.104)	(0.130)		(0.168)	(0.143)
Year*Region			0.468**			0.310
			(0.214)			(0.235)
Year*Education			0.0427			0.210*
			(0.103)			(0.113)
Region		0.173			0.315	
		(0.218)			(0.353)	
Education		0.166			0.447***	
		(0.101)			(0.164)	
Constant	2.127***	1.345***	2.802***	2.623***	2.242***	5.814***
	(0.147)	(0.521)	(0.533)	(0.243)	(0.843)	(0.586)
Fixed Effects	No	No	Yes	No	No	Yes
Observations	124	124	124	124	124	124
Adjusted R-squared	0.027	0.054	0.773	0.016	0.088	0.899

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4. Regression results: Network Density, Network Size

VARIABLES	Network Density			Network Size		
	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.000603**	0.000609**	0.000417	-0.118**	-0.117**	-0.379***
	(0.000294)	(0.000293)	(0.000316)	(0.0568)	(0.0559)	(0.0690)
Log of Efficiency		0.000114	3.36e-05		0.0187	0.0269
		(0.000155)	(0.000167)		(0.0295)	(0.0366)
Year*Region			0.000436**			0.203***
			(0.000217)			(0.0473)
Year*Education			-3.74e-05			0.0567**
			(0.000103)			(0.0224)
Region		-9.90e-06			0.0871	
		(0.000309)			(0.0590)	
Education		-0.000109			-0.0142	
		(0.000145)			(0.0278)	
Constant	0.00311***	0.00293***	0.00314***	0.824***	0.730***	0.986***
	(0.000208)	(0.000743)	(0.000587)	(0.0401)	(0.142)	(0.128)
Fixed Effects	No	No	Yes	No	No	Yes
Observations	98	98	98	98	98	98
Adjusted R-squared	0.041	0.051	0.883	0.042	0.074	0.851

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Cumulative significance tests on *year* for fixed effects models

	H_0: $\beta_1 + \beta_3$*region + β_4*education = 0					
Dependent variable	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Frequency & Detail	-.246	.124	-1.97	0.048	-.491	-.001
Information Type	-.357	.137	-2.61	0.009	-.626	-.088
Network size	-.042	.028	-1.49	0.137	-.098	-.013
Density	.000764	.000130	5.87	0.000	.000509	.001020

Table 6. Regression results: Sector fixed effects and Sector-Year interaction

VARIABLES	Frequency & Detail Index	Type Index	Network Size	Network Density
	(1)	(2)	(3)	(4)
Year	-0.761**	-1.402***	-0.291***	0.000558
	(0.376)	(0.418)	(0.0757)	(0.000355)
Log of Efficiency	0.0606	0.378**	0.0172	1.98e-05
	(0.173)	(0.193)	(0.0360)	(0.000169)
Year*Region	0.215	0.788**	0.163**	0.000553*
	(0.345)	(0.383)	(0.0672)	(0.000315)
Year*Education	0.00214	0.130	0.0643***	-1.72e-05
	(0.110)	(0.122)	(0.0229)	(0.000107)
Sector 12	4.414***	0.733	0.696***	0.00261***
	(0.524)	(1.120)	(0.134)	(0.000896)
Sector 13	1.222*	-0.384	0.0406	0.00141
	(0.725)	(0.970)	(0.146)	(0.00103)
Sector 15	2.778***	1.361	0.928***	0.00261***
	(0.676)	(1.045)	(0.114)	(0.000535)
Year*Sector 12	0.360	-0.163	-0.0830	-0.000373
	(0.319)	(0.355)	(0.0657)	(0.000308)
Year* Sector 13	0.302	0.0493	-0.0279	-0.000329
	(0.393)	(0.437)	(0.0894)	(0.000419)
Year*Sector 15	-0.0268	0.590	-0.168**	-0.000255
	(0.393)	(0.437)	(0.0740)	(0.000347)
Individual Fixed Effects	Yes	Yes	Yes	Yes
Observations	116	116	94	94
Adjusted R-squared	0.938	0.959	0.983	0.981

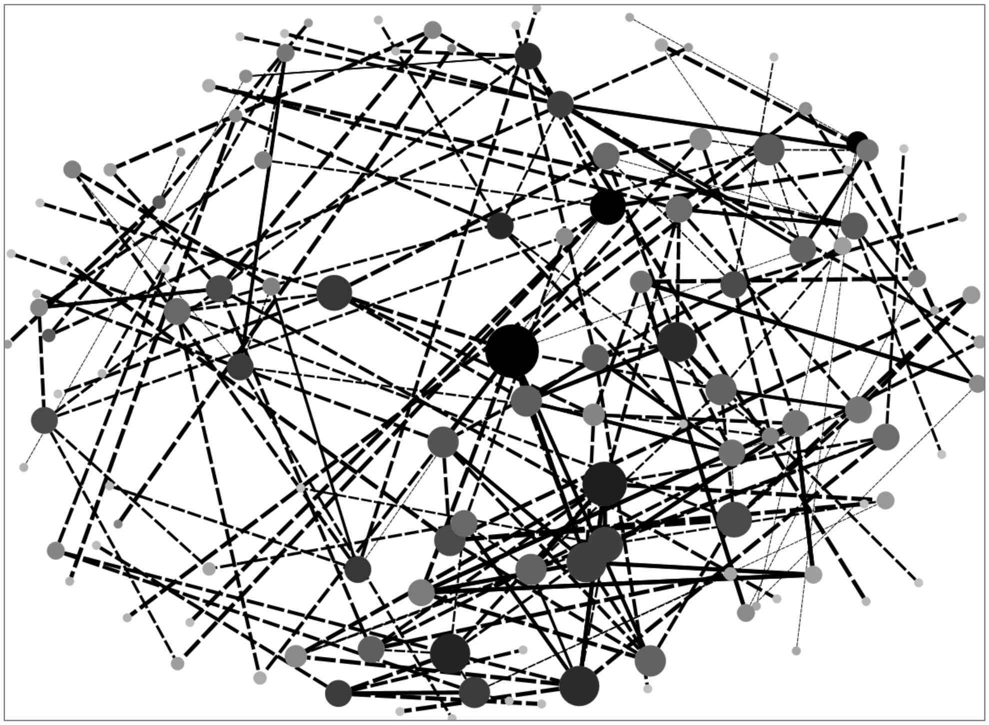
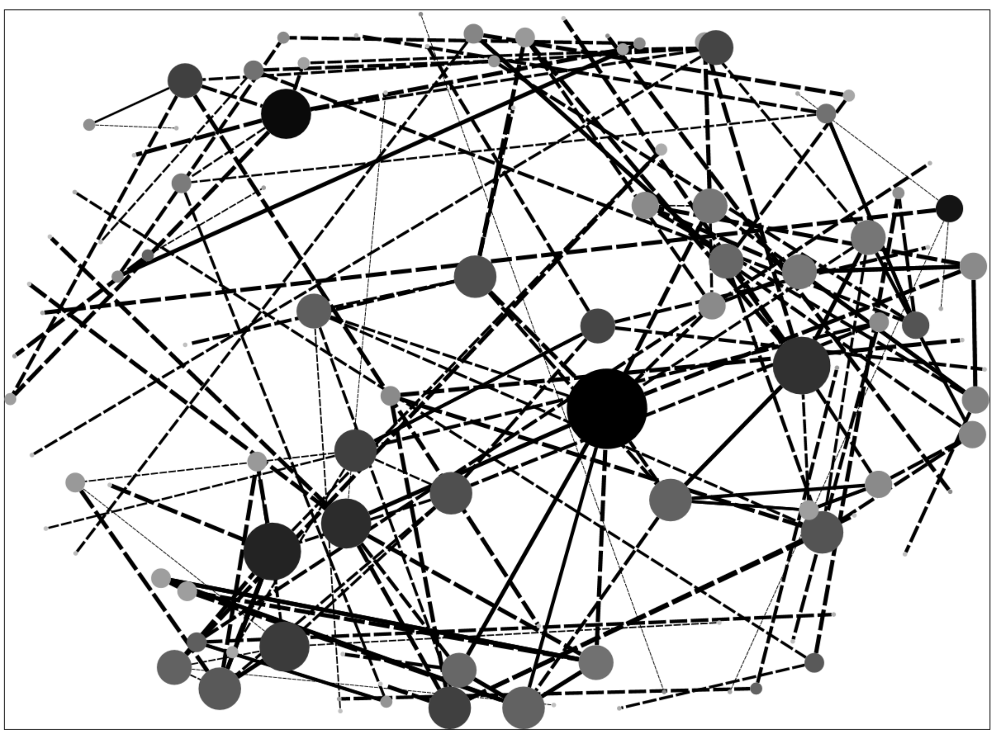


Figure 1. Respondents' network, 2009



Respondents' network, 2010
Source: Author's data

Appendix A.

1. Are you and the following fishermen in the same sector?

	Yes	No
Person #1	☐	☐
Person #2	☐	☐
Person #3	☐	☐
Person #4	☐	☐
Person #5	☐	☐

2. During the **2010** season, on average, how often did you share **specific** information with these fishermen?

	Every day	Every few days	Once per week	Once every two weeks	Once per month	Every two months
Person #1	☐	☐	☐	☐	☐	☐
Person #2	☐	☐	☐	☐	☐	☐
Person #3	☐	☐	☐	☐	☐	☐
Person #4	☐	☐	☐	☐	☐	☐
Person #5	☐	☐	☐	☐	☐	☐

3. When sharing **specific** information with these fishermen during the **2010** season, what kind of information did you share? (check all that apply)

	Market prices	Buyer information	Species composition	Bycatch areas	Specific hot-spots	Gear hazards
Person #1	☐	☐	☐	☐	☐	☐
Person #2	☐	☐	☐	☐	☐	☐
Person #3	☐	☐	☐	☐	☐	☐
Person #4	☐	☐	☐	☐	☐	☐
Person #5	☐	☐	☐	☐	☐	☐

4. Please rate the level of detail of **specific** information that you have shared with these fishermen during the **2010** season:

	1: Low level of detail	2	3	4	5	6	7	8: High level of detail
Person #1	☐	☐	☐	☐	☐	☐	☐	☐
Person #2	☐	☐	☐	☐	☐	☐	☐	☐
Person #3	☐	☐	☐	☐	☐	☐	☐	☐
Person #4	☐	☐	☐	☐	☐	☐	☐	☐
Person #5	☐	☐	☐	☐	☐	☐	☐	☐