Four Essays on Decentralized Markets in Management and Policy

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Abstract

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Governments often create markets to serve management or policy goals. The creation of these markets requires developing the institutional capacity to disseminate market information in order for the market to achieve those goals more effectively. This dissertation draws on prior work regarding network information diffusion to examine the ways in which information brokers affect market function and outcomes in management and policy contexts. The first two chapters focus on the U.S. municipal bond market, which serves as the management context, and uses data on all U.S. municipal bond issues for 2004-2016. The first chapter develops a measure of network connectivity for financial advisors in the market, and shows through linear models under nearest-neighbor matching that these highly connected advisors are associated with reduced interest costs for local governments. The second chapter uses a choice model under state dependence to estimate how local governments' past advisor choices implicitly constrain their future choice sets. The results suggest state dependence could increase interest costs for local governments, particularly for those that have contracted with only one or two advisors in the past. Alaska halibut and sablefish

individual quota fisheries serve as the policy context for chapters 3 and 4 with confidential quota transaction data from AKFIN as the primary data source. In chapter 3, network model simulation shows that quota brokers help traders access the broader market by trading outside of their immediate social network compared to trading without a broker, though there still exists some relationship between traders' social networks and trading patterns even for brokered trades. Brokers are also shown to increase sales price across many quota sub-markets. Chapter 4 develops a novel choice-based method for estimating willingness-to-pay for quota among subgroups. This method is then applied this model within a regression discontinuity design to test how a recent policy change affected resource valuation among key subgroups of interest.

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DEDICATION

To my wife, Alex, for her constant love and support.

EXECUTIVE SUMMARY

Markets explicitly created for the purposes of serving government management or policy goals are ubiquitous, but require an investment in institutions to encourage them to function in such a way that market mechanisms bring about the desired result, and are therefore increasingly becoming the focus of scholarly attention. These created markets are frequently decentralized, without a single central planning mechanism or method to effectively aggregate all market information that would allow a clear market price to emerge. This violates common assumptions of perfectly competitive markets, such as low costs in seeking out market information. Such information costs may lead to difficulty in identifying trading partners and discovering market prices; information that would be required if market participants are to maximize their benefits from market participation.[1]

In this dissertation I examine two such created, decentralized markets; one within a management context and one in a policy context. In a management context, markets are often used to contract out government services. I focus on the particular case of local government participation in the municipal bond market, where local governments may contract out for additional expertise when issuing bonds to fund large projects. Given that the municipal securities market is valued at $3.8 trillion, research into the factors that determine interest costs has the potential to significantly reduce local government debt. In the policy context, particularly in the environmental policy context, markets often take the form of rights-based management of emissions or natural resources. I focus here on the market for Alaskan halibut and sablefish fishing quota. Such fishing quota policies create an implicit right to harvest catch each season, and this right may be bought and sold among

[1] Hahn & Stavins (2011) consider these among the transaction costs associated with thin markets, in addition to bargaining costs as well as monitoring and enforcement costs, all of which might be considered costs due to the lack of perfect information (Dahlman, 1979).

eligible fishery participants. Fisheries in the United States are more frequently being governed by an individual quota system of some form, and understanding how well the market mechanism performs compared to the theoretical expectation has been the focus of comparatively little fisheries economics research.

The common feature of markets across these two contexts is the contingent nature of the market activity, particularly that market participation and outcomes may be based on prior networks of relationships through which market information is transmitted. Network theories attempt to explain how these relationships affect the information a market actor can access, thereby creating heterogeneous market outcomes. In the management context, this outcome would be the costs associated with contracting for the service. In our case in particular, the outcome is a measure of interest costs associated with issuing bonds. In the rights-based management context, the outcome is the price the buyer and seller receive for trading the right, and the ease with which this trade may be accomplished. In an actor-level sense, certain network positions are thought to be advantageous in collecting information or in coordinating behavior (Bodin et al., 2006; Borgatti, 2005). In a dyadic sense, actors that are more proximate in the network are more likely to share market information (Alatas et al., 2016), thereby reducing the search and other information-gathering activities that would necessarily precede a contract in the market.

Without some mechanism to reduce each market participant's information costs, market activity can be very low (Hahn & Stavins, 2011). Additional market actors must often enter to learn information about the state of the market and coordinate market activity before much market activity can take place. Spulber (1999) refers to these actors as market-makers in that they effectively create the market in exchange for a fee from the active market participants. In the context of the municipal bond market, this role is filled by financial advisors who may obtain estimates of the creditworthiness of a bond issue from credit rating agencies, coordinate bond underwriters, and share information on the market with the local government. Most issues are made using a financial advisor, and research shows that interest costs for these issues is significantly lower compared to issues that do not use a financial advisor. In the context of rights-based management policies, permit and quota brokers arise to facilitate trades by identifying trading partners and providing price information to sellers in exchange for a proportion of the total value of the sale. The sulfur dioxide market created by the U.S. Clean Air Act suffered from low trade volume until brokers become involved in the market (Stavins, 1998), and high brokerage use tends to be associated with more efficient markets in quota-managed fisheries (Innes et al., 2014; Newell et al., 2005).

Chapters 1 and 2 focus on the contracting that local governments undertake when issuing debt in the municipal bond market. Previous literature has proposed and shown evidence for two measures of financial advisor quality that decrease expected interest costs for issuers. In chapter 1, I draw on network theories to propose two additional network-based measures, eigenvector centrality and lack of network constraint, which have been thought to be associated with greater information-gathering and openness to innovations, respectively. I hypothesize that a financial advisor that occupies a network position that theoretically allows for greater access to information and greater capacity to coordinate other actors could lead to a decrease in interest costs for the local government that has contracted with them. I use factor analysis to isolate 'experience' and 'network connectivity' factors. Both of these factors are found to be negatively related to interest costs.

In chapter 2, I draw on prior dyadic connectivity literature to estimate the extent to which local governments tradeoff between advisor quality and their prior existing relationships in the bond market. Assuming that information about the market diffuses through bond market relationships, I would expect the relative transaction costs to decrease when governments are proximate to the financial advisor in the network. In fact, I find that local government choice of advisor is strongly driven by previous choice of advisor. This tendency constrains the implicit scope of financial advisors from which a local government may choose and results in higher expected interest costs, particularly among issuers that have contracted with only 1 or 2 financial advisors previously. This dependence on prior decisions may also suppress the subsequent competitiveness of the implicit market among financial advisors for contracts in the bond market. Lack of competition could result in shirking by financial advisors if they are contracting with more insularly-connected local governments. While I propose this possible relationship, I do not test it here and instead plan to address it more thoroughly in future research.

Chapters 3 and 4 focus on the market process associated with selling quota in the halibut and sablefish quota markets. Prior fishing quota market theory shows that under an efficient market, quota price converges to a single value equal to the *in situ* value of the resource. Among the empirical literature that treats quota price as a single value achieved under an efficient market, the presence of highly-publicized and frequently-used brokerage services serves as the rationale for treating the decentralized quota market as if it were a single centralized market. More recent literature has proposed that price and trading activity may be a function of a fisher's characteristics (Jin et al., 2019), in particular that well-connected buyers and sellers may experience a price advantage (Ropicki & Larkin, 2014), and that fishers that are more geographically proximate may be more likely to trade (Björk, 2017).

In chapter 3, I evaluate whether brokered trades for halibut and sablefish fishing quota appear to exhibit characteristics of market efficiency. In particular, I test whether buyers and sellers in the quota markets are independent of other social network ties and whether selling using a quota broker confers a price advantage. Under an efficient market, trades would not be expected to be affected by social ties as that could create arbitrage opportunities between different social groups that a knowledgeable trader could profitably exploit (Jorion & Schwartz, 1986). I adapt a model evaluation procedure from the social network literature to demonstrate that brokered trades are far less correlated with social networks than non-brokered trades. However, there remains some residual social network dependence even among brokered trades compared to the trading patterns that would be expected if quota trading was truly independent of social networks. I further show that this dependence persists across most years of quota trading. This suggests that brokerage in these markets comes close to achieving an efficient market, but still falls somewhat short though I do not judge that this slight deviation from efficiency is sufficient to warrant policy intervention.

One of the hypothesized benefits of adopting a quota policy in a fishery is that it would incentivize the allocation of quota to its most efficient use through the price mechanims. If using a broker consistently led to an increased price and non-brokered quota sales were common in the market, this would imply that quota is being sold to less efficient harvesters, compromising this particular market benefit. I use a linear regression model to show that brokers are associated with higher prices in most halibut and sablefish quota management areas. This suggests non-brokered trades are indeed going to less efficient harvesters. In practical terms, the level of brokerage in this fishery is sufficient that I would not expect this finding to compromise the efficiency gains associated with the policy. However, as the researcher, I do not observe the identity of quota brokers in the data. There remains a possibility that particular brokers are more effective than others at selling quota, which could result in sustained systematic inefficiencies in the market.

In chapter 4, I develop a choice model to explain brokerage use in the halibut fishery and estimate the distribution of willingness-to-pay across different groups of fishers. The heterogenous effects of policy across community sizes has been a topic of concern in the fisheries policy literature, and this model allows the impact of policy on the value different groups place on the fishery to be estimated for community-based subgroups. Among fishers from small communities, willingness-to-pay for quota declines as vessel class sizes increase relative to other fishers. I apply the model in a regression discontinuity research design to estimate the change in willingness to pay as a result of the guided angler fishing policy in 2014. This policy allowed quota transfers to the charter recreational sector, which had previously not been permitted. This policy change was hypothesized to possibly decrease relative willingness-to-pay among small communities due to the relative lack of access to financial services in small communities, which may hinder quota purchases if the quota price increases due to the policy. I find no evidence that small community members were relatively negatively affected by the policy, though there is some evidence that medium-sized community members were. This suggests that similar policies that have been proposed elsewhere may not have a deleterious effect on the most vulnerable participants in the fishery.

Chapter 1

NETWORK CONNECTIVITY AND FINANCIAL ADVISOR QUALITY IN THE U.S. MUNICIPAL BOND MARKET

1.1 Introduction

State and sub-state governmental organizations, such as state agencies, municipalities, school districts, transit authorities, and many others (hereafter, simply referred to as 'local governments'), often issue municipal bonds in order to fund large capital-intensive projects. This requires them to make decisions about who to sell the debt to, how and when, and how to structure the debt while complying with all relevant regulations. Issuing debt involves a series of complex decisions requiring specialized expertise, and the local government rarely has the internal capacity to make those decisions unilaterally. As a result, they convene a 'debt management network' (Miller, 1993) comprised of bond counsels, underwriters, financial advisors and rating agencies in order to issue the debt.

The municipal bond market is largely decentralized, implying potential transaction costs in acquiring new information and creating new contracts between parties. The practice of using rating agencies to provide an assessment of the level of risk associated with the bond is designed to commoditize the issue in some respects. However, the bond is structured separately for each issue, and commodification is limited to the information communicated by the bond rating. In all other respects, the market is decentralized without a formal structure in which issuers can locate underwriters or share price information. Instead, information is distributed, and relationships built between actors in various debt management networks through patterns of shared issues creates a larger network which can then impact the structure of future debt with tangible impacts on local government.

The role of the financial advisor in the debt management network is to work as an agent on behalf of the issuer (Simonsen & Hill, 1998). With the passage of the Dodd-Frank Act, this role has become more formalized as the financial advisor now takes on a fiduciary responsibility toward their client (Bergstresser & Luby, 2018). In essence, the issuer purchases the expertise of the financial advisor when issuing their bond. The quality of the advice an issuer receives from their financial advisor is therefore particularly important as it can have a substantial effect on the interest rates subsequently associated with the issue, and considerable differences in total debt services paid by local governments over the lifetime of the bond as a result.

This paper follows previous literature in estimating the relationship between financial advisor quality and local government interest costs. However, it differs from previous work that has either focused exclusively on financial advisor characteristics in isolation (Allen & Dudney, 2010) or on the ways in which the bilateral relationship between financial advisors and underwriters moderates financial advisor quality (Liu, 2015; Moldogaziev & Luby, 2016) by instead considering financial advisors as embedded within a network of relationships in the municipal bond market. The position of the financial advisor within the larger interconnected bond network affects the information the advisor can readily access and, in turn, the quality of the advice they are able to give to local governments when issuing bonds. However, as yet, the literature concerning how network position of a financial advisor may affect expected interest costs remains sparse. While previous research exists that take network relationships into account (Marlowe, 2013), no study has yet used a national dataset to estimate the relationship between interconnectivity and true interest costs. This paper fills this gap by using a national database of municipal debt issues to estimate the relationship between a financial advisor's connectivity within a larger network of relationships, and expected interest costs of their municipal bond issues during the time period 2004-2016. We find that financial advisor interconnectivity in the municipal bond network is generally associated with lower interest costs, though this relationship is stronger for revenue bonds and for issues that are sold through a negotiated process.

1.1.1 Review of Financial Advisor Quality and Interest Costs

The network of relationships sustained by the financial advisor is particularly important for the issue. They sell their expertise to local governments concerning the timing of the issue, who to sell the debt to, and how the debt should be issued. Using a financial advisor has been shown to lower borrowing costs, underwriter spreads, and reoffering yields for negotiated bonds (Vijayakumar & Daniels, 2006). The quality of this advice can affect outcomes in the bond market (Allen & Dudney, 2010). Because the quality of this advice is predicated upon the information the financial advisor has available and their capacity to coordinate members of the debt management network, the existing interconnectivity between financial advisors and other members of the debt management network may affect the transaction costs associated with selling an issue as well as the financial advisor's access to information relevant to the issue. Previous research has shown that improved access to trade information decreases transaction costs associated with bond issues (Edwards et al., 2007). In this way, bond market outcomes may depend, at least in part, on the social capital these financial advisors can access through their previous relationships with other members of the debt management network - particularly underwriters.

Financial advisor and underwriter quality has often been conceptualized in terms of size rather than the patterns of participation in the bond market. It is thought that a financial advisor will gain expertise through experience with the market, resulting in higher quality advice and lower interest costs as a financial advisor's experience increases (Allen & Dudney, 2010). Network theories suggest that it is not only the direct experience with issuing a bond that affects the quality of advice a financial advisor is able to provide, but also the qualitative connections between financial advisors and underwriters that are formed or reinforced through the process of issuing a bond

Marlowe (2013) investigates the relationship between financial advisor connectedness and true interest costs in the primary bond market for new issues in Washington, California, and Texas, conceptualizing network centrality as a single composite measure. He finds that financial advisors that are more central to the network tend to issue bonds with lower true interest costs. However, the marginal effect was not linear and not statistically significant across all three states. In a study of the secondary bond market (that is, the market comprised of dealers and investors), one of the few other papers that conceptualized bond sales as a network shows that a bond dealer's execution quality increases with network centrality, but that more central dealers charge higher fees as a result (Li & Schürhoff, 2014).

Previous work that uses market-share measures of financial advisor prestige has shown a negative relationship between financial advisor prestige and reoffering yields, particularly for revenue bonds and bonds sold through a negotiation rather than a competitive bidding process (Allen & Dudney, 2010). Similarly, Moldogaziev & Luby (2016) finds a negative relationship between financial advisor market share and true interest costs for negotiated bond issues. Like financial advisors, more prestigious underwriters, as measured by market share, are associated with lower interest costs, particularly for non-investment grade bonds (Daniels & Vijayakumar, 2007).

The relationship between financial advisor quality and interest costs may be moderated by the insularity of the relationships a financial advisor maintains in the municipal bond network. Some researchers have hypothesized that insularity may be beneficial if repeated connections decrease transaction costs of contracting or negotiation between parties through mutual learning (Miller, 1993), particularly for more complex bond issues (Marlowe, 2007). Political network theorists have likewise suggested that network insularity could be associated with high levels of inter-organizational monitoring. If an incentive exists for actors in the debt management network to self-monitor and self-regulate against rent-seeking behavior, high insularity could facilitate those monitoring activities (Berardo & Scholz, 2010).

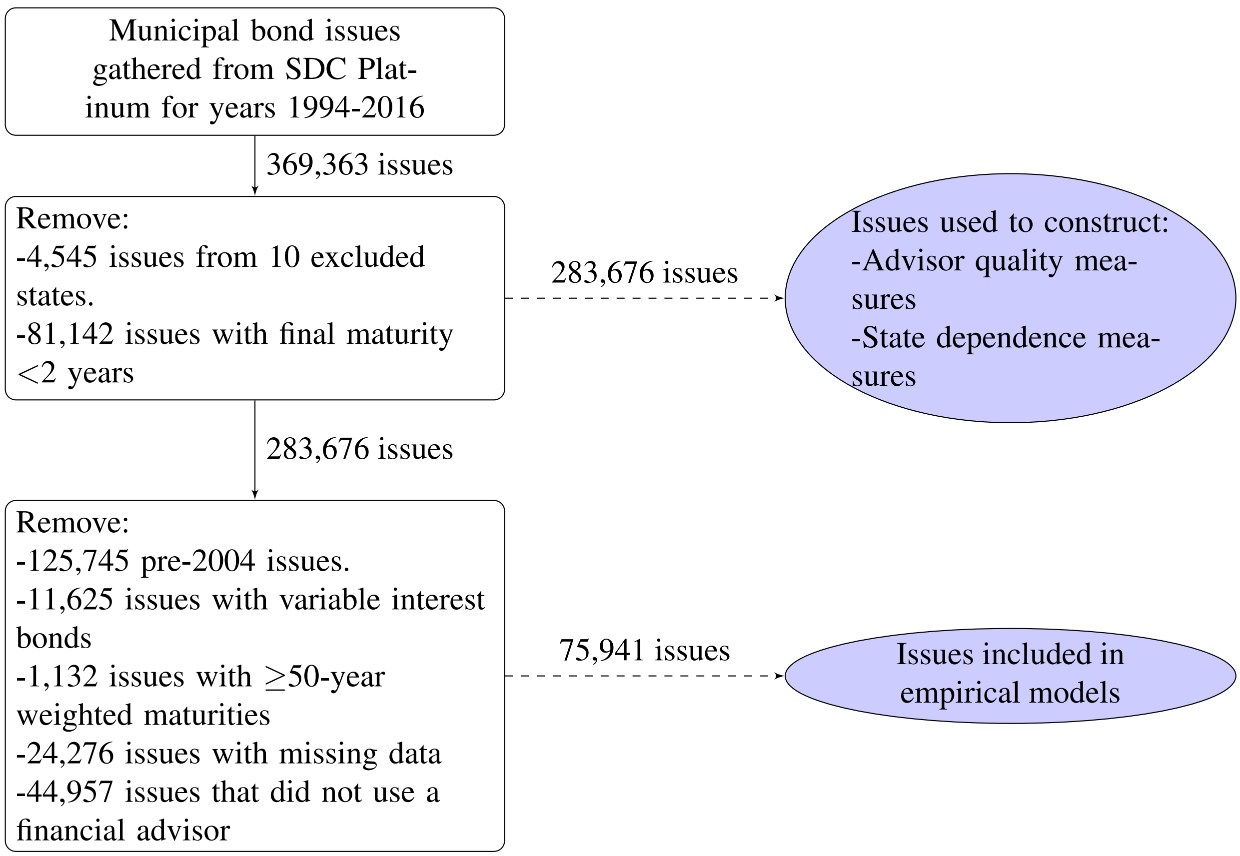
On the other hand, tight-knit network relationships could also be conceptualized as a less competitive market with high levels of market coordination among suppliers, suggesting insular debt management network actors may be able to capture additional revenue from the bond issue through low levels of competition (Brown & Potoski, 2003c; Girth et al., 2012). Miller (1993) finds that insularity results in a lack of learning. While there may be short-term returns to an insular debt management network, there are long-term costs as such network configurations are not conducive to receiving outside information, which was supported by a later case study of the New York Metropolitan Transit Authority debt restructuring program (Miller & Justice, 2011). In a more generalized network case, Burt (2004) similarly conceptualized tightly clustered network relationships as insulating themselves from the diffusion of outside innovation. Empirical research has shown that a closer relationship between financial advisors and underwriters is associated with higher underwriter spreads (Luby & Moldogaziev, 2013) and higher true interest costs (Liu, 2015; Moldogaziev & Luby, 2016), suggesting that more insular relationships may prompt implicit collusion between debt management network actors. Network insularity, measured by the transitivity of network connections, is also negatively associated with the network measure in Marlowe (2013), suggesting a positive relationship between insularity and borrowing costs. Despite some theorizing to the contrary, given these previous results suggests an expectation that greater network connectivity would be negatively associated with interest costs.

1.2 Data and Methods

We retrieved information on new U.S. bond issues from Thomson Reuters SDC Platinum (referred to as 'SDC Platinum') for all issues with sale dates spanning years 1994 to 2016, which includes 369,363 total issues. We excluded from the analysis issues that matured in less than two years. Such a short maturity period makes the issue qualitatively different and such bonds often sell on an alternative credit market. Because measures of financial advisor quality are constructed at the state level, as is discussed in more detail in the following section, issues from six states where local governments issued less than 10 municipal bonds per quarter on average were excluded as being insufficient,[1] leaving 283,676 remaining issues.

All 283,676 bond issues are included in the calculations used to construct the financial advisor quality and state dependence measures of interest. However, the statistical modeling presented below excludes any bond issued prior to 2004. While the full dataset includes bond issues going back to 1994, some data that allows for the calculation of true interest costs (TIC) for an issue, such as issue-specific maturity dates, are only reported regularly in the SDC dataset beginning in 2004. The analysis here focuses on the time period 2004-2016 for which TIC can be reliably calculated (more details on this calculation are reported in the 'Bond Characteristics' subsection below). The statistical analysis further excludes issues with a variable interest rate as ex ante TIC cannot be calculated for these issues. Bonds with with an unusually long maturity of over 50 years (weighted by par value) are also excluded from the final analysis, as are any issues for which data is missing. Of the remaining issues, 62.8% have one or more financial advisors associated with the issue. Because the focus of this paper is on advisor quality and choice, the focus will be on those remaining bonds. A diagrammatic representation of the data processing procedure appears below.

[1]The excluded states are: Alaska, Delaware, Hawaii, Vermont, West Virginia, and Wyoming.



1.2.1 Network Definition and Data

Because the focus of this study is on the network connectivity of the financial advisors, it is crucial to define how the network is measured. Networks more generally are defined by two sets of information: the set of nodes (also called vertices) and the set of links (also called edges) that connect the network nodes. In this case, the network nodes consist of the set of all financial advisors and underwriters involved in the municipal bond market. A pair of nodes is referred to as a dyad. A dyadic link exists between two actors in the network if each actor in the dyad worked on the same bond issue: if one was a financial advisor and one an underwriter or both were underwriters on the same issue.[2] Under this network definition, a shared network link represents a shared experience or set of information that comes from working jointly on a particular issue.

Although financial advisors and underwriters fill different roles in debt management networks, there is not a clear distinction between them in the municipal bond network as a whole. Financial advisors on a bond issue may serve as underwriters on other bond issues. For that reason, the network is defined as unipartite (that is, consisting of a single mode, as opposed to bipartite networks that have two modes) even though the network represents both financial advisors and underwriters.

Following Marlowe (2013), we bound the network at the state level and define each link according to the state in which the shared bond was issued. As a result, the set of network nodes and links will vary between states, creating a distinct network for each state. A node will be present in a state's network only if the organization represented by that node served as a financial advisor or underwriter for a municipal bond issue within that state over the study time period. Likewise, a dyadic link exists in a state's network only if both members of the dyad participated in a common bond issue within that particular state. Although financial advisors may be active in multiple states and carry information across states, there are unique rules in each state that limit the transferability of information, and previous research indicates financial advisors tend to limit their activity to few states (Allen & Dudney, 2010). Even when active in multiple states, financial advisors associated with most municipal bond issues have a distinct local office (Butler, 2008), and analyses of bond markets commonly take place within a single state (e.g., Daniels & Vijayakumar, 2007; Simonsen et al., 2001; Robbins & Simonsen, 2007).

To build the network that prevails at the time of each bond issue, we use the name of each financial advisor and underwriter associated with each issue as reported by SDC Platinum to uniquely

[2]Multiple financial advisors are present for less than 5% of issues. In this case, a link is defined connecting each financial advisor to each other as well as from each financial advisor to each underwriter.

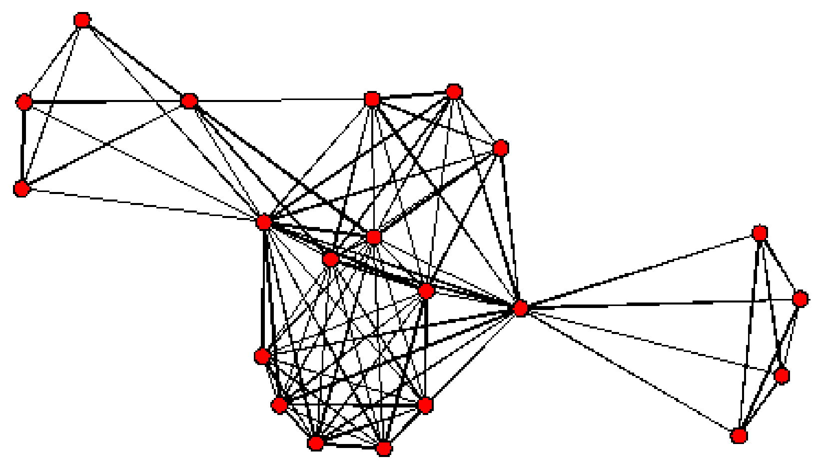


Figure 1.1: Two-Year San Francisco Public Utility bond network (December 2016). Circles represent financial advisors and underwriters. Lines connecting them represent shared bond issues.

identify a particular actor in the bond market. Each state's network is updated on a monthly basis. At the end of a month, the links created due to the bonds sold in that month by an issuer within a particular state are added to the network for that state. All links are assumed to persist for either one or two years, and these links are used to construct one or two-year network measures, respectively. Any link that has not been active for either one or two years is removed at the same time new links are added. This time span corresponds to previous work on financial advisor quality and other bond market network relationships (Allen & Dudney, 2010; Moldogaziev & Luby, 2016; Liu, 2018a).

A visual representation of an example of the financial advisor-underwriter network associated with an individual local government is depicted in figure 1.1. This represents the nodes and links associated with financial advisors and underwriters that participated in bond issues for the San Francisco Public Utility issuer, and is a subset of the full state-level network.

1.2.2 Financial Advisor Quality Measures

One of the focuses of this paper is to estimate the relationship between a financial advisor's network connectivity and the interest costs associated with the bonds they help to issue. However, any estimate of the relationship between network connectivity and interest costs must also control for the known relationship between other measures of financial advisor quality (particularly, market share). To account for the relationship between past financial advisor experience and interest costs, we use the two market share measure of financial advisor quality previously used in the literature (Allen & Dudney, 2010; Moldogaziev & Luby, 2016). In addition to these measures of financial advisor experience, we also use two network measures to account for the position and connectivity of financial advisors in the network: **eigenvector centrality** and **network constraint**.

Eigenvector centrality is often characterized as representing the importance or 'coreness' of a node in the network. A network can be represented as an adjacency matrix. This is a $N \times N$ matrix, where N is the number of nodes in a network. The value of the matrix is one for row i and column j if a link exists between node i and node j in the network, and zero otherwise. In our case, the value equals one if bond market actor i and actor j cooperated on an issue. Eigenvector centrality is calculated by taking the first eigenvector of the network adjacency matrix, which is then scaled from 0 to 1. A node's eigenvector centrality score is positively associated with the number of ties it has as well as the number of ties each node it is connected to has, which implies greater connectivity for the node. Financial advisor eigenvector centrality is generally negatively associated with the interest costs through the network measure in Marlowe (2013) and a dealer's eigenvector centrality is associated with greater search efficiency in Li & Schürhoff (2014). Eigenvector centrality is also related to diffusion centrality, which is a measure of efficiency in spreading information throughout the network (Banerjee et al., 2014).

Network constraint (abbreviated below as **Cnstr**) is derived from the measure described in Burt (2004), and represents the insularity of the node. The constraint measure increases the more that a node's connections are connected to each other and not to other nodes, and has been conceptualized as a measure of how insulated a node is from exposure to outside information or innovation. As network constraint increases, the node becomes increasingly insulated from outside knowledge and is thus less interconnected in the network (Burt, 2004; Lambiotte & Panzarasa, 2009). Formally, constraint is defined as:

$$Cnstr_i = \sum_j (p_{ij} + \sum_q p_{iq} p_{qj})^2, q \neq i, j \text{ where } p_{ij} = \frac{a_{ij}}{\sum_k a_{ik}} \tag{1.1}$$

Where a_{ij} is row i and column j of the adjacency matrix. Network constraint is closely related to 'transitivity'; the proportion of a node's connections that are connected with each other. Marlowe (2013) finds financial advisors with high transitivity to be positively related to interest costs.

In addition to the two network measures, we calculate two market share measures of financial advisor quality (Allen & Dudney, 2010; Moldogaziev & Luby, 2016): (1) the proportion of the par value of municipal bond issues in the state the financial advisor has advised on compared to the total par value of municipal bonds that any financial advisor helped to issue; and (2) the fraction of issues the financial advisor has advised on in the state compared to the total number of municipal bond issues that any financial advisor in the state has advised on. These measures can be thought of as the market share in terms of percentage and market share in terms of number of issues, respectively, relative to the total share of advised issues. Each measure is centered at zero and scaled to one for each state individually to adjust for possible systematic differences in reputation measures by state. These differences are due, most prominently, to variation in state size and corresponding number of financial advisors and number of overall issues within each state. A smaller state will have fewer financial advisors and fewer issuers than a large state, leading to artificially inflated measures of financial advisor reputation in the absence of state-level adjustments.

Because measures of quality would not be expected to endure indefinitely, we define two time periods for each measure, one year and two years before the month in which the issue takes place, to construct eight total variables related to advisor quality and interconnectedness (four measures across two time periods). For network linkages, this means that ties are only included in the network if they were active within the past year or two (that is, the two bond market actors represented by the nodes cooperated on an issue within the past year or two, respectively). That is, each adjacency matrix for each state's one-year network is updated monthly, and $a_{ij} = 1$ if actor i and actor j have cooperated on an issue in the past year and 0 otherwise (likewise, for the two-year network, $a_{ij} = 1$ if i and j have cooperated on an issue within the past two years, and 0 otherwise). For market share measures, only bond issues within the state that occurred within the past year or two, respectively, are included in the calculation.

Multiple financial advisors are listed for a small number of issues, representing less than 5% of the total number of issues that used a financial advisor. In order to avoid making assumptions about either the magnitude of involvement of any advisor or the way different quality financial advisors may interact with one another on an issue, we simply set the financial advisor quality equal to the mean across all financial advisors involved in the issue.

An immediate problem with using these eight variables is the degree to which they are correlated with each other, and the extent to which they reflect the similar underlying latent concepts of advisor quality. While eigenvector centrality represents network position rather than market share, a financial advisor's centrality would be expected to increase as their market share increased because they would be working with more underwriters and would therefore occupy a more central position in the network. Likewise, as the number of links a financial advisor has in the network increases, these links would be expected to be less likely to be connected to each other, thereby reducing network constraint. Although the quality measures are chosen to capture different aspects of financial advisor quality, they do not perfectly isolate the underlying factor of interest.

Table 1.1: Pearson correlations between advisor quality measures.

	Last Year				**Last 2 Years**			
	Share(%)	Share(N)	Eigen	Cnstr	Share(%)	Share(N)	Eigen	Cnstr
Share(%)	1							
Share(N)	0.642	1						
Eigen	0.557	0.559	1					
Cnstr	-0.356	-0.451	-0.615	1				
Share(%)	0.944	0.639	0.556	-0.358	1			
Share(N)	0.626	0.979	0.557	-0.448	0.654	1		
Eigen	0.551	0.573	0.931	-0.644	0.573	0.585	1	
Cnstr	-0.314	-0.400	-0.537	0.900	-0.327	-0.405	-0.599	1

In order to retain and isolate the latent factors of financial advisor quality while reducing the multicollinearity among the eight variables, we follow previous research in using factor analysis to identify underlying latent factors of interest from multiple network measures (Marlowe, 2013; Li & Schürhoff, 2014). We use the 'psych' package in R (Revelle, 2015) to assign factor scores to each advisor on each issue based on two latent factors of advisor quality, with a varimax rotation applied. While factor loadings are sensitive to the number of factors chosen for the factor analysis, two factors are suggested by the underlying motivation behind constructing these measures as reflecting market share and network connectivity of financial advisors. A two factor solution is also suggested based on commonly used choice criteria such as the elbow test and Kaiser criterion.[3]

[3]Factor analysis with three factors rather than two results in a third factor for which no quality measure loads with magnitude greater than 0.5 and the proportion of variance explained by this third factor is under 10%, compared to a two-factor solution with explained variances of 42% and 33% for factors 1 and 2, respectively.

Table 1.2: Factor Loading on Financial Advisor Quality Factors

Measure	Factor 1	Factor 2
Last Year		
Market Share (% of par value)	0.85	0.18
Market Share (% of issues)	0.79	0.31
Eigenvector Centrality	0.53	0.62
Network Constraint	-0.19	-0.92
Last 2 Years		
Market Share (% of par value)	0.86	0.18
Market Share (% of issues)	0.79	0.31
Eigenvector Centrality	0.54	0.66
Network Constraint	-0.16	-0.86
Prop. of Variance Explained	0.42	0.33
Cumulative Variance Explained	0.42	0.75

These two factor scores will be used in the regression analyses rather than the raw measures. The factor analysis results are presented in the table below, and the pattern of factor loadings conform to expectations. Advisor size in terms of both proportion of issues and proportion of par value load highly onto the first factor. Network constraint loads heavily, negatively onto the second factor. Eigenvector centrality loads moderately onto both factors, suggesting that it is related to both market share and interconnectedness. Because factor 1 is mainly associated with market share and centrality in the network while factor 2 relates to the interconnectivity of the node and lack of network constraint in the network, we will refer to factor 1 as the advisor's Experience Factor and to factor 2 as the advisor's Connectivity Factor.

1.2.3 True Interest Cost

The true interest cost (TIC) will be used as a dependent variable in the model as a key outcome measure of the issue for the issuer. The TIC represents the implicit discount rate that equates the payments the issuer must make to the value of the issue, and is widely used in the bond market literature. The TIC is reported for less than 25% of the issues in the SDC data. Instead of using the reported value, we calculate the TIC as the value that solves the following equation:

$$BP - GS = \sum_i \left(\sum_{t \in \tau_i} \frac{1}{2} \times par_i \times coupon_i \times e^{-TIC \times (t - T_0)} \right) + par_i \times e^{-TIC \times (T_i - T_0)} \tag{1.2}$$

The left-hand side of equation (1.2) represents the net proceeds the municipality realizes from the bond issue, equal to the bond proceeds (*BP*) taking into account the gross spread (*GS*) which represents the underwriter fees and other costs associated with the issue. The right hand side represents the two types of discounted payments across all the serial bonds (where each bond in the serial is indexed by i), coupon payments and the payment of the principal at maturity. The set of coupon payment times are indexed by t and is defined by the set τ. These payments are assumed to occur twice per year beginning at the first interest payment date and ending when the bond matures at T_i. The maturity payments are represented by the second term on the right-hand side, and this is simply equal to the discounted par value for each bond in the issue at the time of maturity. Discounting for both coupon payments and the principal is assumed to occur continuously over time, beginning at some 'present' time, indicated by T_0 which is defined as 6 months before the first coupon payment or the time of the issue sale, whichever comes later.

The TIC calculation method presented here differs slightly from other calculations of the true interest cost (e.g., Feldstein et al., 2008) in that future payments are assumed to be discounted continuously rather than biannually. Comparing the two TIC calculation methods to reported TICs suggests that the continuous discounting method used here deviates less from the reported values as measured by root mean squared error, but the differences in calculated TIC between the two methods are very small.

The gross spread is only reported for 42% of the bond issues in the sample. Because such fees typically cause a change in TIC of a fraction of a percentage point, we judge the potential tradeoff in bias from listwise deletion of these observations to be greater than the potential for these data to significantly bias the TIC calculations. We use multiple imputation conducted in the Amelia II package in R (Honaker et al., 2011) to impute 10 values for each missing gross spread observation, and then use these imputed gross spread values to calculate 10 sets of all-in-TIC measures.

1.2.4 Control Variables

Linear model estimates of true interest costs as a function of financial advisor experience and network connectivity control for a variety of bond characteristics, issuer type, and public information on assessed risk. These variables are summarized in table 1.3. Because the focus is on advisor choice and advisor quality, only issues that included a financial advisor are included in calculating the descriptive statistics. All variables listed are also found in SDC Platinum dataset of US municipal bonds. The control variables we chose are suggested by the previous literature and have been utilized in previous studies of outcomes in the municipal bond as a function of debt management network actor characteristics (Allen & Dudney, 2010; Liu, 2018a; Marlowe, 2013; Moldogaziev & Luby, 2016).

Previous work has relied on measures of market-level factors to control for changes in the bond market over time. We largely circumvent these considerations by using a monthly fixed effect in order to control for any month-to-month changes in the overall market conditions. We include the Bond Buyer 20 index as a distinct benchmark for the general obligation and revenue bond market interest rate, assigned to the respective bond type, to capture any changes in market conditions that may differentially affect bond types. However, market-level processes should be captured by controlling for month of issue and state in which the local government is located.[4]

Par value may decrease TIC on average due to decreasing marginal costs associated with underwriting activities (Marlowe, 2013), though empirical estimates have often shown a positive relationship between interest cost and par value (Bland, 1985; Moldogaziev & Luby, 2016). Mean par value for issues in the sample is just over $25 million. As the distribution of par values displays a highly positively skew, we take the usual step using a natural log transformation of the par value which results in a distribution of issue size that is near normal. Longer issues carry greater risk, suggesting a positive relationship between TIC and maturity date which agrees with previous empirical work (Allen & Dudney, 2010; Moldogaziev & Luby, 2016). 20 years represents the modal period to final bond maturity in the sample of issues. However, because bonds comprising each issue may mature at different times, we control for years until issue maturation by weighting the final maturation of each bond in the serial by the proportion of par value represented by the issue. The average issue maturation period, weighted by par value, is between 10 and 11 years.

Repayment source is controlled for by a binary variable indicating whether the bond was a revenue bond, with general obligation bond as the reference category. Because GO bonds are backed by the full faith and credit of the local government, revenue bonds entail higher risk which would be expected to result in a somewhat higher TIC. We follow previous literature in including both taxable and tax exempt bonds in the sample when estimating the empirical models with a binary variable indicating bonds that are taxable and those that are subject to the alternative minimum tax, with tax exempt issues serving as the reference category.[5]

[4]This specification does not account for the possibility of jointly-varying state- and time-varying effects. We estimate an alternative specification where state- and time-varying effects are jointly captured through state-specific b-splines. We define the b-spline as a cubic basis function with annual knots to control for changes over time. Based on adjusted R-squared and AIC, this specification is not preferred compared to the model specification with additive month and state fixed effects, and the results are largely unchanged.

[5]While the dynamics of taxable and tax-exempt bonds have diverged somewhat in recent years and they largely sell in distinct markets, the inclusion of taxable bonds in the sample follows previous literature (e.g., Liu, 2018a). As

We also control for method of sale with a binary variable indicating whether the bond was issued by a competitive bidding process with negotiated sales as the reference category. Previous research has indicated that competitive sales significantly reduces interest costs to issuers (Liu, 2018a; Simonsen & Robbins, 1996; Simonsen et al., 2001). It is unclear to what extent method of sale is truly exogenous to the model as a financial advisor would be expected to advise the issuer on method of sale. High quality financial advisors would be expected to know that competitive bid sales would result in lower TIC, and would therefore be more likely to choose this method when advising on a bond issue. While method of sale is included in the linear model to measure the direct relationship between financial advisor quality factors and interest costs, it is possible there are some indirect effects of financial advisor quality on interest cost through changes in probability of using particular methods of sale which would dampen the true relationship between financial advisor quality and TIC.

Credit rating is a ubiquitous measure of credit-worthiness, and we would expect bonds with higher credit ratings to have lower TIC as they would be expected to entail lower risk. Credit ratings from three different firms are reported in the data; Moody's, Standard & Poor's, and Fitch. Credit worthiness of a bond issue is constructed through four aggregate measures, triple-A rating, double-A rating, single-A rating, and triple-B to junk bonds, with unrated issues as a reference category. Many bond issues have ratings from more than one of the credit rating firms, and bonds within the issue may receive different credit ratings. Rather than assign the issue to a particular category, the issue is assigned a value within each category representing the proportion of the issue's par value that was assigned the particular rating. For example, if an issue consisted of two bonds of

a robustness check we re-estimated the empirical models of true interest costs presented in Section 1.3.2, excluding issues that contained taxable bonds. The magnitude of the coefficients on the financial advisor quality variables stayed the same or marginally increased for these models compared to the estimates that included taxable bonds. Because the tax exempt-only split sample results do not differ qualitatively from the main results, we do not present them here, but they would be available upon request.

equal size, one rated triple-A and one rated double-A, then the issue would be assigned the value 0.5 for both triple-A and double-A, and zero for all other categories. In case of disagreement between bond rating firms for a single issue, the rating is averaged equally across the different rating firms. For 6% of issues, there is large disagreement between bond rating firms, in which case it is considered a split rating in the SDC Platinum database. Because this large disagreement might cause uncertainty that could lead to greater expected risk, we further control for this split rating with an additional binary variable.

1.3 Empirical Model of Financial Advisor Quality

1.3.1 Model definition

I incorporate the factor scores generated by the factor analysis above into a linear model of true interest costs as a function of advisor quality as well as the control variables. As mentioned in Section 1.2 any issues that did not have a financial advisor listed are removed as advisor quality is only relevant to issues that used a financial advisor. Results of the ordinary least squares regressions are presented in table 1.4. All models include state-level and monthly fixed effects though these coefficients are not reported in the table.

While each regression produces a single estimate and standard error, it represents a combination of regressions across 10 datasets produced by the multiple imputation procedure, each with a slightly different TIC. To produce a single set of empirical results, the least squares model is run on each dataset separately. The coefficients and standard errors are then combined to form a single regression result using the rules outlined in Rubin (2004). Prior to estimation, the TIC values are winsorized based on the mean of the TIC value for each observation across multiply imputed datasets, retaining observations that lie in the middle 98 percentiles of TIC values for each year in

Table 1.3: **Description and Descriptive Statistics of Municipal Bond Characteristics.** Dataset includes all bond issues for which there was a financial advisor reported and no missing data values for years 2004-2016.

Measure	Mean	SD	Description
True Interest Costs	3.41	1.28	The discount rate that equates the principal and interest costs associated with the issue to its price.
Bond Buyer Index	4.36	1.20	A benchmark interest rate (specifically, for 20-year GO or Revenue bonds, respectively).
Total Par Value (log)	16.11	1.58	The natural log of the total par value of the issue across all bonds in the serial.
Average Maturity Year	10.48	5.28	The mean maturity period for all bonds in the serial weighted by par value.
Percent Par Insured	0.26	0.43	The proportion of the total par value that is insured.
Revenue Bond	0.36	0.48	=1 if the bond issued was a revenue bond, =0 if the bond was a GO bond.
Competitive Bid	0.50	0.50	=1 if the bond was sold through competitive bid process, =0 if bond was sold through negotiated bid process.
Callable	0.78	0.41	=1 if a bond is callable (can be redeemed prior to maturity).
Refunding	0.43	0.49	=1 if a refund bond (a bond refinancing measure).
Sinking Fund	0.37	0.48	=1 if issuer holds a sinking fund account to ensure debt service payment availability.
Bank Qualified	0.41	0.49	=1 if loan is bank qualified.
Taxable	0.10	0.30	=1 if bond purchases are subject to regular taxation.
Alt. Min. Taxable	0.01	0.12	=1 if bond purchases are subject to alternative minimum tax.
Split Rating	0.06	0.24	=1 if the credit risk of the bond was rated significantly differently by Moody's and S&P.
Bond Rating			As rated by Moody's, S&P, and Fitch.
AAA/Aaa	0.29	0.44	The proportion of par value rated AAA or Aaa.
AA/Aa	0.44	0.48	The proportion of par value rated AA or Aa.
A	0.12	0.31	The proportion of par value rated A.
BBB/Baa or below	0.02	0.16	The proportion of par value rated BBB or Baa or lower.
Issuer Type			
Municipality	0.31	0.46	=1 if issuer is a city, town, or village.
College/University	0.02	0.14	=1 if issuer is a college or university.
District	0.37	0.48	=1 if issuer is a district, such as water or school districts.
Local Authority	0.11	0.32	=1 if issuer is a local authority, such as building authority or airport.
State Authority	0.09	0.29	=1 if issuer is a state authority, such as state water department.
State Government	0.02	0.15	=1 if issuer is a state government.
No. of States	44	-	
No. of Issues	75,941	-	

order to control for extreme outliers due to any errors in data reporting.

Model (1) presents a baseline model that regresses true interest costs on characteristics of the bond, the bond issue, and the bond issuer, but excludes characteristics related to the financial advisor. Model (2) repeats model (1) but also includes the two advisor-level quality factors: issuer experience and connectivity. Some of the observed factor scores, particularly the connectivity factor score, can take on large values. In model (3) we control for possible non-linearities in the relationship between quality factors and TIC, particularly, the possibility of dminishing marginal returns to advisor quality, by estimating a model with truncated financial advisor quality factor scores. We restrict the factor score to the range [-3,3], rounding any score below -3 or above $+3$ to equal -3 and $+3$, respectively, in order to reduce the influence of factor score outliers to influence the estimated relationship between advisor quality and TIC. Model (4) presents an alternative definition of the advisor quality factors. Rather than allowing them to take on continuous values, the quality measures are each grouped into three bins: low quality (bottom quartile), middle quality (second and third quartiles, serves as reference category), and high quality (top quartile).[6]

Due to the non-random nature of financial advisor quality, the relationship between financial advisor quality and true interest cost may be confounded by a number of other unmeasured factors. The primary barrier to drawing causal inferences concerning the relationship between TIC and financial advisor quality is the non-random selection of financial advisors of differential quality by issuers. There is an element of choice in the local government's selection of a financial advisor, and local governments that may on average achieve a lower TIC may also select financial advisors that would be considered higher quality according to the advisor experience and interconnectivity

[6]While these models treat state- and time-varying factors as additively separateble, we report an alternative model specification in the appendix that control for state-specific time-varying factors but are otherwise similar to models (2) and (3). Because the results are only marginally different, we do not report these results in the main body of the paper.

quality measures defined here.

Natural experiments that utilize timing of a policy change as a discontinuity from which to draw inferences can be the most convincing, but this is not feasible in a context such as this when advisor quality is not subject to exogenous policies. One method for enhancing the strength of causal inferences is a two-stage model that uses a Heckman correction. The first stage of the model estimates the probability of a local government using a high quality financial advisor in order to issue their debt, while the second stage incorporates the inverse Mill's ratio of the first stage into the linear regression of issuer outcomes on financial advisor qualtiy to obtain an unbiased estimate of the second stage (Allen & Dudney, 2010; Moldogaziev & Luby, 2016).

A procedure that can similarly serve to improve causal inferences is matching in order to reduce the imbalance in observed distributions between the 'treated' and 'untreated' data prior to regression, reducing the dependence of causal inferencing on model assumptions. While many such methods exist, we use Mahalanobis Distance Matching. This is a method that matches untreated observations to treated observations with replacement based on the match that will minimize the Euclidean distance across all normalized values in the treated and untreated observation. This method approximates a fully blocked experimental design, and is therefore more effective than propensity score matching in reducing imbalance in the multivariate probability distributions and the associated model dependency (King & Nielsen, n.d.). The output is a set of weights for each observation, that equals one for all treated data, zero for any unmatched control observations, and equal to the total number of matches scaled to sum to the number of total control observations for any matched control observations.

In this case the 'treated' observations were those issues that had the financial advisor quality factor at or above the 75th percentile; that is, a high quality financial advisor according to these measures, while the 'untreated' observations were those issues that had a low quality financial advisor, falling at or below the 25th percentile according to the relevant advisor quality metric. The middle two quartiles of the data were removed to create a clear delineation between issues with financial advisors of differential quality. State was exactly matched, so that only issues within a state could be matched with each other. A state was skipped if a Mahalanobis distance could not be calculated, indicating a singular or near-singular data matrix. Matching was repeated for each quality measure separately for the full sample as well as for each of four split sub-samples: revenue bonds, general obligation bonds, negotiated issues and issues sold through competitive bid.

1.3.2 Empirical Results

While the current literature has focused primarily on financial advisor experience in terms of market share as a measure of financial advisor quality, the results in table 1.4 suggest that the network connectivity of financial advisors is at least as important in terms of relationship to true interest costs. Both financial advisor quality factors, experience and network connectivity, are consistently associated with a negative relationship with true interest costs, suggesting that an issuer that uses a more experienced or more well-connected financial advisor will see a reduction in their lifetime interest payments. To contextualize the magnitude of the relationship, a financial advisor in the highest quartile of experience has an average experience factor score of 1.27 while the average factor score for the lowest experience quartile is -1.17. This implies the expected reduction in true interest costs associated with using a financial advisor in the highest experience quartile rather than the lowest is roughly 4.8 basis points across both model (2) and model (3). Moving from the bottom quartile of the connectivity factor score (mean of -0.99) to the upper quartile (mean of 0.64) is associated with a reduction in interest costs of roughly 4.9 basis points in model (2) and 6.8 basis points in model (3). Because model (3) reduces the influence of outliers, this suggests that

Table 1.4: **Regression of True Interest Cost on Bond and Advisor Characteristics.** State and monthly fixed effects are included in the regression but not reported. All standard errors are Huber-White robust standard errors with degrees of freedom correction, and clustered at the issuer level.

Regressors	(1) Est.(SE)	(2) Est.(SE)	(3) Est.(SE)	(4) Est.(SE)
Experience Factor		**−0.021 (0.003)**	**−0.020 (0.003)**	
Low Quality				**0.002 (0.007)**
High Quality				**−0.061 (0.008)**
Connectivity Factor		**−0.030 (0.004)**	**−0.041 (0.004)**	
Low Quality				**0.042 (0.007)**
High Quality				**−0.038 (0.007)**
(Constant)	3.210 (0.071)	3.199 (0.071)	3.200 (0.071)	3.210 (0.071)
Bond Buyer Index	0.010 (0.002)	0.009 (0.002)	0.009 (0.002)	0.010 (0.002)
Total Par Value (log)	−0.001 (0.003)	0.000(0.003)	0.000 (0.003)	0.000 (0.003)
Average Maturity Year	0.059 (0.001)	0.058(0.001)	0.058 (0.001)	0.058 (0.001)
Percent Par Insured	0.235 (0.008)	0.232(0.008)	0.232 (0.007)	0.232 (0.007)
Revenue Bond	0.163 (0.009)	0.163 (0.009)	0.163 (0.009)	0.163 (0.009)
Competitive Bid	−0.164 (0.007)	−0.152 (0.007)	−0.151 (0.007)	−0.153 (0.007)
Callable	0.534 (0.009)	0.534 (0.009)	0.534 (0.009)	0.533 (0.009)
Refunding	−0.193 (0.006)	−0.192 (0.006)	−0.192 (0.006)	−0.192 (0.006)
Sinking Fund	0.322 (0.007)	0.321 (0.007)	0.321 (0.007)	0.321 (0.007)
Bank Qualified	−0.201 (0.008)	−0.200 (0.008)	−0.200 (0.008)	−0.201 (0.008)
Taxable	0.927 (0.013)	0.928 (0.013)	0.928 (0.013)	0.928 (0.013)
Alt. Min. Taxable	0.156 (0.031)	0.151 (0.031)	0.150 (0.031)	0.149 (0.031)
Split Rating	-0.062 (0.011)	-0.058 (0.011)	-0.058 (0.011)	−0.056 (0.011)
Bond Rating				
AAA/Aaa	−0.823 (0.017)	−0.818 (0.017)	−0.816 (0.017)	−0.814 (0.017)
AA/Aa	−0.575 (0.017)	−0.570 (0.017)	−0.569 (0.017)	−0.568 (0.016)
A	−0.252 (0.017)	−0.251 (0.017)	−0.250 (0.017)	−0.249 (0.017)
BBB/Baa or below	0.459 (0.026)	0.441 (0.026)	0.442 (0.026)	0.452 (0.026)
Issuer Type				
Municipality	−0.048 (0.011)	−0.047 (0.011)	−0.047 (0.011)	−0.047 (0.012)
College/University	−0.104 (0.028)	−0.114 (0.028)	−0.115 (0.028)	−0.111 (0.028)
District	0.078 (0.011)	0.080 (0.011)	0.080 (0.011)	0.079 (0.011)
Local Authority	0.051 (0.016)	0.047 (0.015)	0.046 (0.015)	0.049 (0.015)
State Authority	0.014 (0.027)	0.007 (0.027)	0.004 (0.027)	0.007 (0.026)
State Government	−0.088 (0.024)	−0.088 (0.025)	−0.091 (0.025)	−0.091 (0.024)
N	74,906	74,906	74,906	74,906
R^2	0.811	0.811	0.812	0.812
Adj. R^2	0.810	0.811	0.811	0.811
AIC	118684	118383	118342	118365

Note: All control variable coefficients are statistically significant at the 5% level across all models except for total par value and state authority issuer type.

there may be some outlying connectivity factor scores that are affecting the estimate. The magnitude of these estimates is about the same as the estimate generated by Allen & Dudney (2010), which estimated a reduction of 3.5 basis points of interest cost associated with a high-quality advisor compared to a low-quality advisor when advisor quality is measured by number of issues, and a reduction of 2.6 basis points when advisor quality is based on volume of issues.

Model (4) suggests any gains from using a more experienced financial advisor comes only from the highest experience factor category. There is essentially no difference in expected true interest cost by using a medium-quality and a low-quality financial advisor in terms of experience according to these results. By contrast, when financial advisor quality is measured through network connectivity, the expected decrease in true interest cost when using a medium-quality financial advisor compared to a low-quality advisor is roughly the same as the expected decrease associated with replacing a medium-quality advisor with a high-quality financial advisor. The results suggest a somewhat greater reduction in true interest costs compared to models (3) and (4) which use a continuous measure. Model (4) suggests an expected reduction of 6.3 basis points and 8.0 basis points from using a high quality advisor compared to a low quality advisor based on the experience and interconnectivity quality factor, respectively.

Because the inferences being drawn from these models are focused on the advisor quality characteristics, we refrain from discussing the results of each of the control variables. We merely note that due to the number of issues included in the models, nearly all the coefficients are statistically significant, and the direction and magnitude is generally consistent with previous empirical work on the relationship between true interest costs and characteristics of municipal bond issues. An exception is the very small magnitude of the coefficient on the Bond Buyer Index, but this is simply due to the monthly fixed effects absorbing nearly all of the variation over time rather than the benchmark yield.

1.3.3 Matching and sub-sample splits

The results from the matched and unmatched split sample results appears in Table 1.5. For the unmatched samples, our results match the findings reported in Allen & Dudney (2010) that the relationship between TIC and financial advisor experience is stronger for revenue bonds compared to general obligation bonds and for negotiated issues compared to competitively bid issues, as evidenced by the greater magnitude coefficients associated with the advisor quality factor for the revenue bonds and negotiated issues. This matches the expectation advanced here, and in the previous literature more broadly, that financial advisor quality has a greater impact when the advisor is participating in more complex bond issues. Moving from a ‘low experience’ advisor (lower quartile of advisor issues) to a ‘high experience’ advisor (upper quartile) is associated with a 4.1 basis point reduction in expected TIC for general obligation bonds compared to a 7.4 basis point reduction for revenue bonds. Likewise, a high experience advisor is associated with a 2.7 basis point reduction in TIC for competitive issues, and a 5.4 basis point reduction for negotiated issues compared to a low experience advisor.

The matching procedure, which is designed to reduce modeling assumptions and improve causal inferences from these models exacerbates this observed pattern with respect to the advisor experience factor. Focusing on the matching procedure that matched each issue that used a highly experienced advisor to issues that used a low experience financial advisor and that were otherwise as close as possible in other issue characteristics, the coefficients on the experience factor remain largely unchanged from the unmatched results for the more complex bond issues: revenue bonds and negotiated issues. However, for the less complex sub-samples, the coefficient on the advisor factor is considerably reduced, suggesting a 1.9 basis point reduction in TIC for GO bonds when using a high experience advisor (as compared to 4.1 for the unmatched sample), and no benefit from using a high experience advisor when the issue is sold through a competitive bid process.

Cumulatively, this suggests that any advantage local governments gain from using a highly experienced financial advisor may only be evident for more complex bond issues.

Despite previous hypotheses that narrower insularity may contribute to learning for more complex bond issues, a similar pattern observed for the experience factor is also observed for unmatched issues for the connectivity factor: namely, that the relationship between advisor network connectivity and expected TIC is much more evident for samples that contain more complex bond issues. Moving from a relatively unconnected advisor (lower connectivity factor quartile) to one that is highly connected (upper connectivity factor quartile) is associated with a 6.4 basis point reduction in TIC for revenue bonds, but only a 2.8 basis point reduction for general obligation bonds. Similarly, highly connected financial advisors would be expected to be associated with a 6.1 basis point reduction in TIC for negotiated issues compared to a 1.3 basis point reduction for issues sold through competitive bidding. Unlike the experience factor, however, the coefficients associated with the connectivity factor for general obligation bonds and competitive issues change relatively little when matching is applied. In fact, the coefficient associated with connectivity factor for competitive issues increases in magnitude from -0.010 to -0.016, implying a 2.1 basis point reduction in TIC through using a highly-connected advisor relatively to one with low connectivity.

1.3.4 Advisor Quality Before and After Dodd-Frank

The passage of the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank), represents a potential point of discontinuity in the relationship between financial advisor quality measures and municipal bond market outcomes. Among the regulatory concerns addressed by Dodd-Frank is the quality and independence of the financial advice that the financial advisor is providing the local government (Bergstresser & Luby, 2018). To address these concerns, Dodd-

Table 1.5: **Regression of True Interest Cost on Advisor Quality Based on Matched and Sub-Sample Splits of Full dataset**. All variables included in the models presented in table 1.4 are included in each regression, in addition to state and monthly fixed effects, but only the coefficient on the financial advisor quality variable that was the focus of the matching procedure is presented here. All standard errors are Huber-White robust standard errors with degrees of freedom correction, and clustered at the issuer level.

Issue Subsets	Number of Issues	Matching Based on Advisor Quality Factor	Experience Factor	Connectivity Factor
All	73,159	None	-0.021 (0.003)	-0.030 (0.004)
	22,533	Experience	-0.016 (0.001)	
	22,120	Connectivity		-0.023 (0.002)
Revenue Bonds	25,668	None	-0.030 (0.006)	-0.035 (0.005)
	7,808	Experience	-0.028 (0.001)	
	7,540	Connectivity		-0.028 (0.001)
General Obligation Bonds	47,491	None	-0.017 (0.003)	-0.020 (0.004)
	13,963	Experience	-0.008 (0.001)	
	14,004	Connectivity		-0.020 (0.001)
Negotiated Issues	36,314	None	-0.022 (0.005)	-0.034 (0.004)
	11,777	Experience	-0.022 (0.001)	
	10,038	Connectivity		-0.022 (0.001)
Competitive Issues	36,845	None	-0.011 (0.003)	-0.010 (0.005)
	9,542	Experience	0.001 (0.001)	
	10,766	Connectivity		-0.016 (0.001)

Frank added a new requirement that financial advisors register with the Securities and Exchange Commission (SEC) and the Municipal Securities Rulemaking Board (MSRB). It also granted the MSRB regulatory authority over financial advisors, which had heretofore been subject to few formal regulations or licensing requirements, and prevents other members of the debt management network from providing the local government with advice. Critics of the rule have argued that registration places a burden on financial advisors that could cause advisors to exit the market, thereby reducing competition among financial advisors and creating oligopolistic market conditions with potentially detrimental effects for local government issuers (Johnson, 2013). Such a scenario could result in reversing the empirical results above if advisor quality was channeled into inceasing fees rather than increasing the quality of financial advice. However, what little empirical work has been done on the impacts of Dodd-Frank suggest the opposite is the case. In a study of municipal bond issues in California before and after the municipal advisor registration was implemented, Ivonchyk (2019) finds that true interest costs for bonds issued with a municipal advisor decreased after the municipal advisor rule went into effect.

The SEC adopted the final rules for municipal advisor registration on September 20, 2013, but the rule was temporarily stayed until July 1, 2014 at which time a phased-in compliance period was in place until October 31, 2014. Thus, the full registration requirement was not in full effect until November 1, 2014. To test whether the relationship between quality measures and true interest costs has shifted significantly since the implementation of the financial advisor registration rule, we split the sample into two equal periods, and re-run the regression model (3) on the two samples separately. What we define as the pre-adoption period encompasses 26 months, ending when the final rule is adopted on September 20, 2013, and beginning on June 20, 2011. The post-implementation period begins when the final rule is fully implemented after November 1, 2014 and lasts until December 31, 2016.[7] Excluding the post-adoption, pre-implementation period prevents the estimation results from being contaminated from any anticipatory effects from the rule.

The results of the regressions are presented in Table 1.6. The magnitude of the relationship between advisor quality and TIC declines for both quality factors, although this decline is marginal for the experience quality factor and not statistically significant for the connectivity factor. These results suggest that any change in the relationship between financial advisor quality and true interest cost as a result of the municipal advisor rule has been negligible in the short term. While the changes in coefficients between pre-adoption and post-implementation may be the result of random changes to the bond market, given the direction of the results it is worth further detailed research in both the short- and long-term.

1.4 Discussion and Conclusion

The results described above offers several implications for local governments and offer new insights into how these local governments make a key decision when issuing debt: who to choose as a financial advisor. In general, the empirical results in the model of true interest cost clearly demonstrates the importance of choosing high quality financial advisors to participate in the debt management network, and the implications of this choice for the debt burden of local governments. More importantly, this research adopts a network perspective to present a different aspect of what characterizes a 'quality' financial advisor in the bond market context. Specifically, a financial ad-

[7]An alternative approach is to keep the sample pooled and add an interaction between each of the two financial quality variables and a binary variable indicating that the issue occurred after November 1, 2014. However, testing the estimated coefficients on the control variables for the pooled estimate compared to the split sample estimate revealed considerable differences in the relationship between control variables and TIC. In particular, in the post-registration period bonds the relationship between a bond's credit ratings and TIC were weaker, as was the relationship between weighted maturity year and TIC, perhaps reflecting lower perceived risk from investing in the bond market.

Table 1.6: **Regression of True Interest Cost on Advisor Quality for Pre-Adoption Period and Post-Implementation Period of the Municipal Advisor Rule**. All variables included in the models presented in table 1.4 are included in the regression in addition to state and monthly fixed effects, but only the coefficients on financial advisor quality are included here. All standard errors are Huber-White robust standard errors with degrees of freedom correction, and clustered at the issuer level.

	Dependent Variable: True Interest Cost		
	Pre-Adoption	Post-Implementation	P-value for Pre/Post differences
Experience Factor	−0.014	−0.012	0.782
	(0.006)	(0.004)	
Connectivity Factor	−0.052	−0.042	0.212
	(0.010)	(0.007)	
N	13,496	17,546	
R^2	0.775	0.741	
Adj. R^2	0.773	0.740	

visor that is highly interconnected in the bond market may be as or more valuable in achieving low interest payments than a more experienced financial advisor. Conversely, choosing a financial advisor that is more insulated within a tight-knit cluster of debt management network actors tends to result in higher interest costs for the issuer. This is somewhat akin to previous work on the deleterious consequences of 'network stability' (Luby & Moldogaziev, 2013; Miller, 1993; Moldogaziev & Luby, 2016), though the perspective adopted here is not simply dyadic: all else equal, a financial advisor who has worked to issue bonds with other debt management network actors who are not highly connected with each other will tend to achieve lower interest costs for the bonds they help to issue.

Following Moldogaziev & Luby (2016), this paper also tests the hypothesis advanced in Marlowe (2007) that for more complex bond issues, insularity in the bond market network can lead to mutual learning that may help to more advantageously structure complex issues such as revenue bonds. Specifically, Moldogaziev & Luby (2016) suggests extending the Marlowe (2013) paper on network centrality as a way of measuring the impact of the complexity on true interest costs. Using this network-based approach, and in contrast to the mutual learning hypothesis but in agreement with Moldogaziev & Luby (2016), the results indicate that, if anything, using a financial advisor with a high degree of network interconnectivity leads to lower true interest costs for revenue bonds and negotiated bonds compared to general obligation bonds and competitively issued bonds, respectively. Based on the split sample regression results, it would be expected that using a financial advisor with highly insular network connectivity would result in a 4.9 or 4.6 basis point increase in TIC for revenue bonds based on the unmatched and matched regressions, respectively. Although, it should be noted that the results presented here do not consider the relationship between the financial advisor and the set of underwriters used for a particular bond issue, rather it measures the financial advisor's network connectivity in terms of all the underwriters (and financial advisors) the advisor has previously worked with.

Chapter 2

FINANCIAL ADVISOR NETWORKS AND SELECTION IN THE U.S. MUNICIPAL BOND MARKET

2.1 Introduction

When local governments fund large public projects beyond the scope of current tax revenue, they issue debt in the form of municipal bonds. These bonds are purchased by underwriters and resold on the secondary market. Much as in other government contracting contexts, competition among underwriters to purchase municipal bonds is thought to encourage competition and drive down debt service costs (Guzman & Moldogaziev, 2012; Robbins & Simonsen, 2007; Simonsen & Robbins, 1996). When issuing debt, local governments may also contract with a financial advisor to purchase the advisor's expertise concerning the structure and timing of the bond issue as well as negotiate with, or gather bids from, underwriters (Vijayakumar & Daniels, 2006). Financial advisors are likewise service contractors that are employed to reduce the government burden in investing in internal financial management capacity. As we saw in the previous chapter and in previous empirical work (Allen & Dudney, 2010; Liu, 2015; Moldogaziev & Luby, 2016), the choice of financial advisor may appreciably affect interest costs of the bond. However, choice of financial advisor, particularly the effective scope over which local governments choose a financial advisor, has not been the subject of much scholarly attention.

Given that previous research has identified financial advisor characteristics that systematically reduce interest costs for local governments, it is puzzling why issuers do not consistently use these ‘high quality’ financial advisors when issuing debt. Research on similar public debt management puzzles has suggested status quo bias or decision inertia, the tendency of people or organizations to stick with a previous decision, as a possible explanation for apparently sub-optimal decisions (Liu, 2018b). In this paper, we use a conditional logit choice model to estimate the probability that a local government will choose each particular financial advisor as a function of advisor quality as well as their previous contracting relationship with the financial advisor within the municipal bond market. This allows us to estimate the implicit value that issuer’s place on their prior relationships when seeking out a financial advisor for a new issue. Our results reveal the implicit size of each local government’s market for financial advisors based on their previous interactions with the municipal bond market. In addition to revealing local government contracting behavior, this leads to practical guidance for local governments when choosing from among financial advisors to reduce their dependence on previous choices and foster an implicit competitive market. This reliance on previous choices to drive current decisions is referred to as ‘path-dependence’ in the theoretical social science literature (North, 1990; Page et al., 2006), and modeled as a form of ‘state-dependence’ in the choice modeling literature (Heckman, 1981; Seetharaman, 2004). We follow the choice modeling literature hereafter to refer to is as state-dependence more generally.

State-dependence narrows the scope of likely financial advisors. To seek out an alternative financial advisor outside of the scope of their prior contracting relationships, the local government would have to bear the transaction costs in order to develop the contract-management capacity (Brown & Potoski, 2003a) to expand their scope of potential financial advisors and to evaluate the quality of their assistance in issuing debt. Local government bond issuers then face a direct tradeoff between investing in contract management capacity and possible higher interest costs on debt due to receiving low quality advice.

Beyond this direct tradeoff, there exists a possible secondary consideration. State-dependence reduces the number of potential financial advisors an issuer is likely to contract with, leading to an implicit lack of effective market competition among advisors. Market competition among government service contractors is frequently seen as a fundamental necessity in achieving competitive market prices (Bel et al., 2010) and in maintaining accountability among contractors. High market competition is one of the main motivators behind the decision to contract out services (Hefetz & Warner, 2011). However, service contract markets that are highly decentralized, thin, or otherwise noncompetitive are common in the market for government contracts (Johnston & Girth, 2012). The prevalence of thin markets among government vendors could risk compromising the potential efficiency gains from contracting out services (S. R. Smith & Smyth, 1996), either due to vendor market power or due to shirking and the inability to credibly punish poor vendor performance (Brown & Potoski, 2003a; Girth et al., 2012). While thin vendor markets may be partially the product of implicit barriers to entry in the form of large up-front investments in non-transferable capital required for delivering services (Globerman & Vining, 1996; Brown & Potoski, 2005), they are also the result of the government's capacity for managing the contracting market (Brown & Potoski, 2004). If a local government's choice of financial advisor in the municipal bond market is largely driven by previous decisions and there has been little variety in their previous choices, this could cause a lack of competition that leads to relatively poor performance, even if they contract with a high quality advisor.

It is worth noting here that a parallel literature has challenged the theory that market competition among vendors leads to successful delivery of high-quality services at low cost to the government. High levels of market competition by itself does not necessarily produce positive outcomes (Lamothe & Lamothe, 2009; Brunjes, 2019). And, some researchers have emphasized relationships between public and private service providers (Hartley et al., 2013), including collaborative network approaches to governance (Milward et al., 2009). Empirically testing these competing theories is a topic for an extension of this research.

2.1.1 State Dependence and Financial Advisor Choice

If using particular financial advisors offer an opportunity for decreasing expected interest costs associated with an issue, why don't local governments all use a more experienced and highly connected financial advisor when issuing bonds? One plausible explanation is that the previous financial advisor choices that a local government has made coupled with the patterns of network connectivity within the municipal bond market alters each issuer's implicit costs of seeking out and contracting with particular financial advisors.

A wealth of prior research shows that individuals and organizations tend to maintain the status quo, retaining the same choice even when confronted with new information or a new environment (Tripsas & Gavetti, 2000; Samuelson & Zeckhauser, 1988). With respect to financial advisor choice, in particular, while anecdotal evidence suggsts local governments attempt to account for quality when searching for financial advisor services (Allen & Dudney, 2010, p. 389), there is also strong tendency among local governments to re-use the same financial advisor they used for their most recent bond issue (Allen & Dudney, 2010; Moldogaziev & Luby, 2016). Remaining in the municipal bond context, Liu (2018b) shows evidence for status quo bias among issuers with respect to method of sale.

Local governments may issue debt multiple times and have the opportunity to work with a financial advisor for each issue. While the status quo may be influential in a local government's choice of financial advisor, state dependent models provide a more flexible alternative by incorporating the full history of a local government's financial advisor choices into the choice model. State dependence models have been extensively used in estimates of how an individual or household's decision to purchase a particular brand of product is related to their 'state' as determined by their sequence of past choices, where the influence of each previous choice decays as it becomes more remote (Guadagni & Little, 1983; Seetharaman, 2004). If the decay rate is very high, it suggests the decision-makers value only the most recent past, and the choices look like a pure status quo decision-maker who only values the most recent previous decision. Research in a wide variety of other domains such as fishing location choice in commercial fisheries (M. D. Smith, 2005) and labor market participation (Hyslop, 1999) have also shown decisions to be made based on the decision-marker's full history rather than just maintaining the most recent status quo.

2.2 State Dependence Measures

I define three state-dependent measures based on the network connectivity between an issuer, financial advisor, and other members of the debt management network: **(i)** whether a financial advisor has previously advised the issuer, **(ii)** whether an issuer has used that financial advisor before in an underwriting role, **(iii)** how connected is the financial advisor to the issuer through underwriters in the bond network.

2.2.1 Advisor Connectivity

Following the previous literature on choice inertia and state dependence, issuers would expect to be more likely to select a financial advisor again if they had chosen them to work on a previous bond issue. This direct link in the bond market network is represented as Y_{njt}^{FA}, defined as the number of bonds that local government n has issued that advisor j served as financial advisor in the previous year, t. This aggregates the financial advisor choice at the annual level which allows the measure to be more tractable in a large choice model.

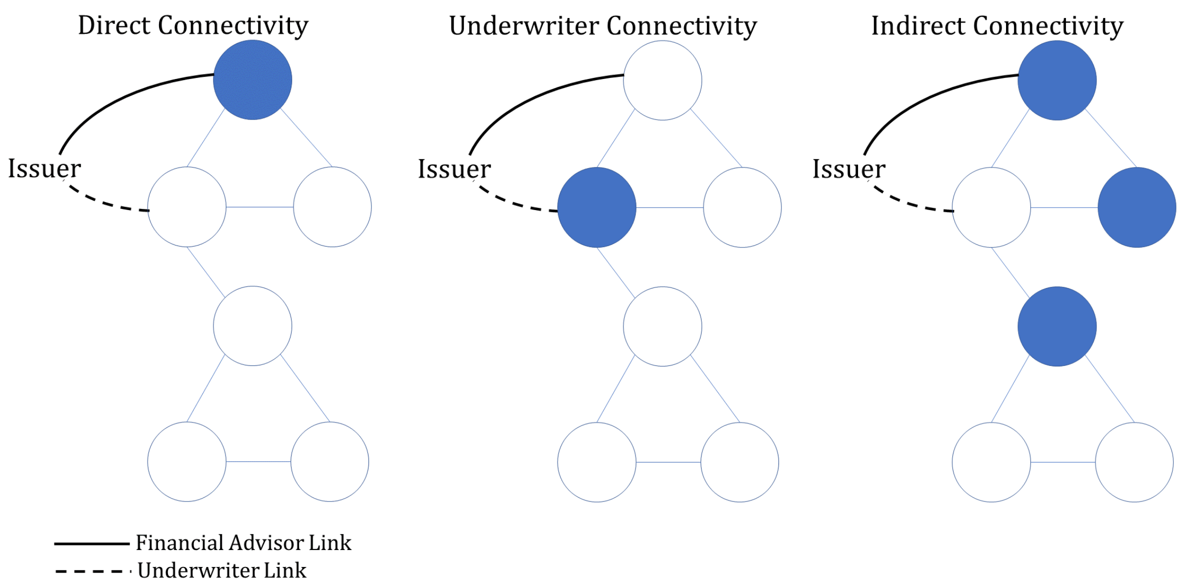


Figure 2.1: Graphical representation of the three state dependent measures for a single example bond network. Filled circles in each network represent the network actors that are connected to the issuer through the respective state dependent measure.

Y^F_{njt} = Number of bonds issuer n has issued with j as financial advisor in the past year.

2.2.2 Underwriter Connectivity

Previous authors have described the common practice of a financial advisor turned underwriter, where a financial advisor may also serve as an underwriter on the same issue. While financial advisors are no longer permitted to resign and become underwriters since the passage of Dodd-Frank and the modification of rule G-23, organizations that have served as underwriters may continue to also work as financial advisors on other issues. An issuer may be inclined to search among the previous underwriters they have worked with when searching for a financial advisor as familiarity between the parties may reduce the search and negotiation costs associated with seeking out a new financial advisor. The link with a financial advisor who has previously worked with a local government as an underwriter is represented as Y^U_{njt}, defined as the number of bonds that local government n has issued that advisor j served as underwriter in the year prior to month t.

Y^U_{njt} = Number of bonds n has issued with j as underwriter in past year t.

2.2.3 Indirect connectivity

Finally, a financial advisor may be indirectly linked to a local government through an underwriter. Evidence for the potential for this process to shape a local government's choice of financial advisor comes from network research more generally, rather than from the municipal bond literature. There is a large body of evidence that indirect links through a third party tend to close; two nodes that were once connected through a third node become directly connected (Goodreau et al., 2009), and indirect effects shape the spread of information in a network (Alatas et al., 2016; Zhang et al., 2018). The indirect effect is defined by Y^{Ind}_{njt}, and represents the indirect link between the local government n and advisor j through the underwriters the local government has previously used. It is equal to the number of bonds the local government n has issued through a particular underwriter, defined as above by:

$Y^{U}_{nrt} =$ Number of bonds n has issued with r as underwriter in past year t.

This term is multipled by the average connectivity between that underwriter and financial advisor j over the past two years, defined as $Y^{U-FA}_{rjt'}$. Two years is chosen here to match the time frame in the bond market network defined previously, and matches previous work on financial advisor-underwriter connectivity (Allen & Dudney, 2010; Moldogaziev & Luby, 2016; Liu, 2018a). [1]

$$
\begin{aligned}
Y^{U-FA}_{rjt'} =& \text{Number of bond issues underwriter } r \text{ has worked on with} \\
& \text{advisor } j \text{ as underwriter in the two years prior to the month of the current choice } t'.
\end{aligned}
\tag{2.1}
$$

Formally, the indirect connectivity measure is defined as:

$$
Y^{I}_{njtt'} = \sum_{r} \left(Y^{U}_{nrt} \times \frac{Y^{U-FA}_{rj,t'}}{\sum_k Y^{U-FA}_{rk,t'}} \right) \tag{2.2}
$$

The first term represents the strength of the tie between an issuer n and underwriter r over the past year. In the second term, $Y_{rjt'}$ equals the number of issues that financial advisor j worked with underwriter r with during the previous two years. So the second term represents the strength of the tie between the underwriter r and financial advisor j during that time, normalized over ties

[1] An alternative specification of this measure used a single year of connectivity between underwriter and financial advisors rather than two years. Results were qualitatively identical between the two measures, and the two year time span resulted in a marginally greater log likelihood than the measure that used just 1 year of underwriter-advisor connectivity data. For clarity, the two year measure is the only one presented here.

Table 2.1: Mean state dependence value for each advisor-issue pair by year prior to the year the issue takes place. Note: these values do not apply normalization or choice decay that will be incorporated in the choice model.

	Years before issue									
Measure	0	1	2	3	4	5	6	7	8	9
Advisor (Selected)	1.70	1.56	1.36	1.18	1.02	0.93	0.83	0.74	0.66	0.59
Advisor (Not Selected)	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.01
Underwriter (Selected)	0.04	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.05	0.05
Underwriter (Not Selected)	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.03	0.03
Indirect (Selected)	2.78	2.85	2.38	2.08	1.71	1.52	1.34	1.17	1.06	0.93
Indirect (Not Selected)	0.11	0.11	0.10	0.10	0.09	0.08	0.07	0.06	0.06	0.05

between underwriter r and all financial advisors. Finally, this indirect connectivity is summed over all underwriters to provide a net measure of indirect connectivity between the local government and the financial advisor through every possible underwriter link. While this specification is somewhat unwieldy, it allows for connectivity between issuer and underwriter, represented by the first term, to take place on a different timeframe than the network connectivity between the underwriter and financial advisor in the second term.

Table 2.1 summarizes the mean values for each of the three connectivity measures for the financial advisors chosen by the local government to issue the bond as well as those that were not selected. While these are descriptive statistics rather than a choice model and does not include the choice decay or normalization procedures, it does show that particularly the advisor and indirect connectivity measures are much greater on average for advisors who were selected to participate in the issue compared to those that were not. While not conclusive, does this provide some cursory evidence that local governments find their financial advisors among the set of advisors they are connected to within the municipal bond network.

2.2.4 State Dependence and Choice Decay

To incorporate each measure of connectivity into a state dependence measure that takes into account the history of an issuer's connectivity with each financial advisor in the bond market network, we implement a state dependence procedure based on Guadagni & Little (1983). State dependence at the time t of each choice is defined based on the exponentially weighted average of previous choices. This allows a sequence of the issuer's previous choices to be incorporated into the model to capture not just a local government's bias toward the status quo, but also estimate how much their more distant past choices influence their present. Because the data includes 10 years of issues prior to 2004 when true interest costs becomes available, we allow for a ten-year time horizon for the state dependence measure. That is, choices made within the past ten years are incorporated into the measure, but are removed thereafter.[2]

More formally, for each connectivity measure Y^S, where S consists of the set $\{F,U,I\}$ representing advisor connectivity, underwriter connectivity, and indirect connectivity, respectively, there exists a corresponding state dependence measure X^S formally defined by:

$$X^S_{njt} = \frac{\sum_{\tau=0}^{9}(1-\delta)^{\tau} Y^S_{nj,t-\tau}}{\sum_{k\in K_m}\sum_{\tau=0}^{9}(1-\delta)^{\tau} Y^S_{nk,t-\tau}}, S \in \{F,U,I\} \tag{2.3}$$

Where δ represents choice decay; the proportionate decrease in influence of each successive choice. For each local government, the state dependence measure is normalized to account for differences in rates of issue, unless an issuer has yet to select a financial advisor in which case their

[2] Some models of state dependence, such as M. D. Smith (2005) incorporate the entire time horizon for which there is data and estimate an initial condition for each choice alternative. However, these models tend to be limited to 10 or fewer alternatives, whereas the model we estimate here includes more than 20 alternatives within each state, making the estimation of an initial condition computationally intractable.

state dependence is set to the inverse of the number of financial advisor alternatives for that state.

Financial advisor state dependence (X_{njt}^{F}) and underwriter dependence (X_{njt}^{U}) can therefore be thought of as an average of financial advisor choices of advisor and underwriter, respectively, over the past 10 years, weighted according to how many choices were made in a given year and exponentially weighted by the number of years since the choices occurred, and normalized to sum to 1 across all alternatives for each choice (Guadagni & Little, 1983). The state dependent representation of indirect connectivity incorporates the ten-year history of an issuer's interactions with an underwriter, but in accordance with previous research that has focused on one or two-years' worth of financial advisor interactions on the bond market, the underwriter-financial advisor link remains fixed in the past two years. It can therefore be thought of as the current connectivity of a financial advisor to an underwriter, weighted by the issuer's previous choices of underwriters over the past 10 years, likewise exponentially weighted by years since the choice occurred and normalized to sum to 1 across all choice alternatives.

2.3 Choice Model

We use a conditional logit specification (McFadden, 1974) to model the local government's choice of financial advisor for each bond issue. Under the random utility model (RUM) framework, each issuer n is faced with a choice of financial advisor j that results in some indirect utility U_{nj}, which has some observed component V_{nj} and some random component ε_{nj} that is unobserved by the researcher. The local government selects advisor j as their financial advisor only if $U_{nj} > U_{nk}$ $\forall k \neq j$. Under the assumption that ε_{nj} is independently and identically distributed for all nj with distribution of generalized extreme value type-I (Gumbel) distribution,McFadden (1974) shows the probability that issuer n will select financial advisor j takes a logit form.

This requires us to specify a utility function for local governments in choosing their financial advisor. As we know from previous research, governments report trying to identify the financial advisor that will provide them with the lowest interest cost (Allen & Dudney, 2010). More generally, local governments attempt to monitor the behavior of their service providers and correct for poor performance (Brown & Potoski, 2003b). Cumulatively, this suggests that, to the extent that the local governments are aware of the quality of the financial advisor, that they will use that information in their contracting decision. Advisor quality is a characteristic of the advisor. While this measure varies across the set of advisors, it is invariant to which local government is making the choice - each issuer within each state is presented with the same set of possible financial advisors and the quality of each does not vary based on the issuer. We use the same two measures of quality here that were developed in the previous chapter ('experience factor' and 'connectivity factor'). Even if these measures are not causally related to quality, the results presented in the previous chapter show evidence that they are related and are therefore an indicator of quality regardless of the causal direction.

Furthermore, we hypothesize that the incentive to select a high quality financial advisor will be relatively strong if the size of the issue were relatively great. We interact each measure of quality with the issuer-normalized log of total par value to capture any change in preferences for advisor quality for larger issues.

We also include a binary variable to indicate that the advisor has not been active in the past year. This accounts for financial advisors that may be relatively inactive. While this is captured somewhat by the quality measures, the binary variable improves model fit by allowing a discontinuous relationship between quality measure and utility for those relatively inactive advisors.

Together, these five measures (the two quality factors, the two interactions with par value, and the binary variable to capture recent inactivity) comprise an advisor-level quality term, denoted V_j^Q.

In addition to advisor-level characteristics, we incorporate the state dependence measures introduced in the preceding section and which we hypothesize would reduce the transaction costs associated with additional contracting. These state dependence terms include the advisor, underwriter, and indirect state dependence measures outlined in the previous section. We denote this term V_{nj}^S. Notice that the quality term is indexed by advisor j while the state dependence term is indexed by issuer n and advisor j.

We model choice of financial advisor as a function of these two aggregate observed components V_j^Q and V_{nj}^S plus the unobserved component ε_{nk}. Thus, j will be selected by n if and only if:

$$V_j^Q + V_{nj}^S + \varepsilon_{nj} > V_k^Q + V_{nk}^S + \varepsilon_{nk} \forall j \neq k \tag{2.4}$$

We define the subset of alternative financial advisors over which a choice is made is defined at the state level.[3]. The number of choice alternatives for each state are displayed in figure 2.2.

Advisors' experience and interconnectivity factors as well as the state dependence an issuer faces varies by month, resulting in a probability of local government n in state m using financial advisor j for an issue in month t defined by a logit with the following general form:

$$P_{njt} = \frac{e^{V_{jt}^Q + V_{njt}^S}}{\sum_{k \in K_m} e^{V_{kt}^Q + V_{nkt}^S}} \tag{2.5}$$

V_{jt}^Q denotes the experience and interconnectivity of advisor j at month t described in Section 1.2.2.

[3]While logit models often assume a constant set of alternatives, McFadden (1974) specifies a more general form that allows a set of alternatives for each choice.

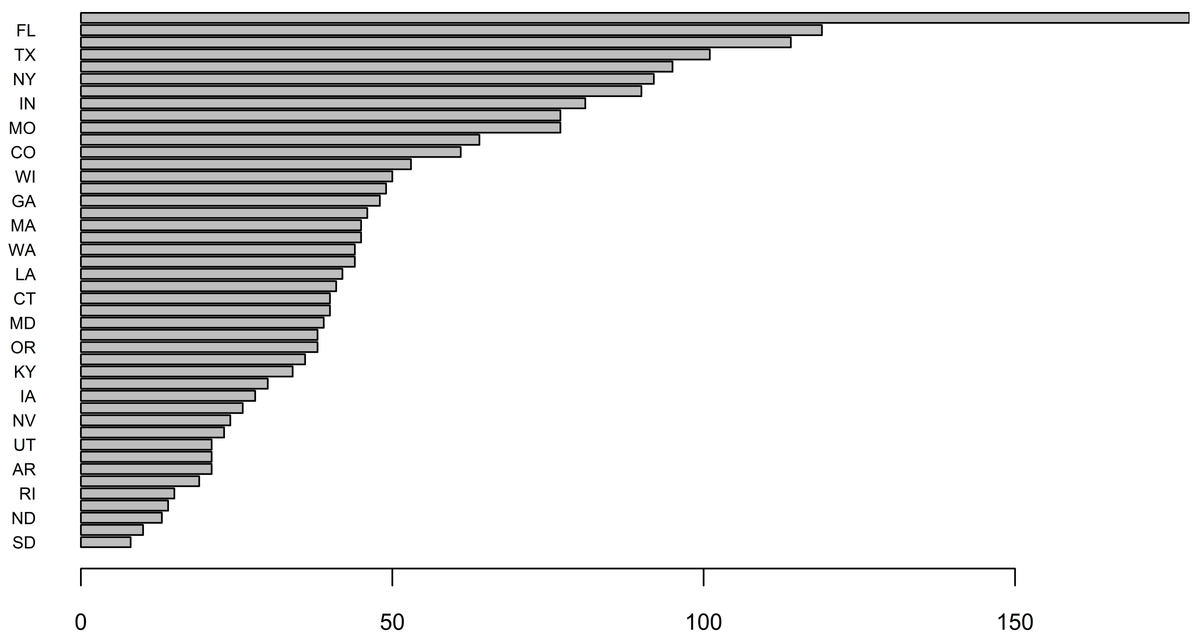


Figure 2.2: Number of financial advisors that helped issue municipal bonds by state over the period 1994-2016.

V^S_{njt} refers to the state dependence of issuer n with respect to financial advisor j at month t, which is described in detail in the following sub-section. Parameter estimates are obtained through maximum likelihood estimation of the joint probability of all choices in the data, with the usual log transformation.

$$\text{Log Likelihood} = \sum_{n,t} \sum_{j} Y_{njt} \times \ln(P_{njt}) \tag{2.6}$$

Where Y_{njt} equals 1 if financial advisor j was used on the issue (issued by local government n in month t) and zero otherwise.[4]

Because some states have well over one hundred financial advisors selected at least once during the years 1994-2016, this has the potential to cause a poor model fit for those rarely-chosen alternatives. As we would expect these rarely-chosen alternatives to also have a lower advisor quality factor scores, which may artificially bias the estimates upwards. As a robustness check, we run an alternative model specification that includes only the 20 most frequently used financial advisors in each state in the choice set, and remove any observation from the dataset for which a financial advisor outside of this more limited choice set was selected. This procedure removes just 8% of the observed issues while reducing the number of financial advisor alternatives in the choice set by 78%.

[4]More than a single financial advisor is chosen for less than 5% of issues. In that case, we treat each financial advisor selection as an independent choice where the financial advisor chosen maximizes the issuer's utility, essentially treating the two (or more) financial advisors as equally maximizing utility over the choice set. The choice is then weighted by the inverse of the number of financial advisors chosen in order to equalize the weight of choices across all issues. The results presented below are not sensitive to this procedure. Other methods for dealing with multiple selections, such as using one of the selections at random and removing the other chosen alternative from the list of alternatives produce nearly identical results. While it would be possible to model the joint decision, this is not the focus of the paper given the relatively few issues with multiple financial advisors.

2.4 Choice model results

The results from the logistic regression models are presented in table 2.2. The first thing to note, is that the results support previous anecdotal evidence that issuers consider advisor quality when choosing from among financial advisors. The coefficients for both advisor quality measures are consistently positive and statistically significant across the model estimates. However, the estimated relationship between advisor quality and choice becomes weaker when the model accounts for additional state dependence measures. Model (1) in table 2.2 includes only the financial advisor state dependence. When underwriter and indirect state dependence are included in model (2), the coefficients for both advisor quality measures declines somewhat. This holds for all estimates in table 2.2; when more state dependence measures are included, the coefficients on advisor quality are somewhat lower, though this effect is more pronounced for the experience factor than for the connectivity factor. To put this reduction in perspective, for model (1), the estimated probability of choosing a financial advisor from the highest quartile of experience quality factor is 3.62 times the probability of choosing the same financial advisor from the lowest quartile of experience quality factor, but using the results for model (2) it is only 2.77 times as likely an advisor will choose the high quality advisor compared to the low quality.[5] This result is perhaps unsurprising as higher quality financial advisors would also be expected to be more closely-connected to issuers, but it does suggest that choice of a high quality financial advisor may be a by-product of the advisor's advantageous connectivity in the bond network rather than due to the local government's purposeful choice of a quality advisor.

As the choice set becomes more restrictive in models (3) and (4) and as the set of issuers becomes

[5]Mean experience factor score is 1.27 for the high quality advisor, compared to a low quality mean experience factor score of -1.17, making the odds ratio is roughly equal to $e^{0.527\times(1.27+1.17)} = 3.62$, compared to model (2) where the estimated probability of choosing a highest quartile advisor in terms of experience is $e^{0.418\times(1.27+1.17)} = 2.77$.

Table 2.2: **Logit model of advisor choice.** Multinomial logistic regression of choice of financial advisor as a function of advisor-level quality factors and state dependent measures of connectivity between issuer and financial advisor.

	Dependent Variable: Chosen financial advisor					
	(1)	(2)	(3)	(4)	(5)	(6)
Experience factor	0.527^{***}	0.418^{***}	0.444^{***}	0.318^{***}	0.346^{***}	0.150^{***}
	(0.005)	(0.007)	(0.006)	(0.007)	(0.008)	(0.011)
Connectivity factor	0.522^{***}	0.471^{***}	0.420^{***}	0.360^{***}	0.333^{***}	0.260^{***}
	(0.005)	(0.006)	(0.007)	(0.008)	(0.010)	(0.011)
Exp. factor×Par	-0.014^{**}	-0.014^{**}	-0.007	-0.006	-0.014^{*}	-0.013^{*}
	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)
Conn. factor× Par	-0.028^{***}	-0.028^{***}	-0.074^{***}	-0.075^{***}	-0.081^{***}	-0.083^{***}
	(0.006)	(0.006)	(0.008)	(0.009)	(0.009)	(0.009)
Inactive Past Year	-2.047^{***}	-2.018^{***}	-1.704^{***}	-1.652^{***}	-1.450^{***}	-1.353^{***}
	(0.020)	(0.020)	(0.031)	(0.031)	(0.040)	(0.040)
State Dependence						
Advisor	4.978^{***}	4.828^{***}	4.504^{***}	4.328^{***}	4.823^{***}	4.587^{***}
	(0.013)	(0.014)	(0.013)	(0.014)	(0.016)	(0.017)
Underwriter		0.577^{***}		0.355^{***}		0.044
		(0.036)		(0.031)		(0.042)
Indirect		1.394^{***}		1.460^{***}		1.893^{***}
		(0.046)		(0.044)		(0.066)
Choice Decay	0.623	0.632	0.618	0.630	0.596	0.604
	(0.025)	(0.026)	(0.029)	(0.030)	(0.027)	(0.028)
Choice Set	All	All	Top 20	Top 20	Top 20	Top 20
Issuers	All	All	All	All	Freq.	Freq.
Num. Choices	96,252	96,252	91,123	91,123	67,092	67,092
Adj. R^2	0.695	0.697	0.676	0.678	0.751	0.754
Note:						$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

more limited in models (5) and (6), the estimated relationship between advisor quality and choice of financial advisor weakens. Models (3) and (4) limit the choice set to only the 20 most frequently used financial advisors in each state rather than the full set of advisors used over the 2004-2016 time period. This preserves more than 80% of the choice observations while also reducing the number of alternatives by 80%, thereby reducing the effect of advisors that are used infrequently and accounting for the possibility that an advisor may only sporadically participate in the bond market. Because the advisors that were removed are simultaneously less likely to be chosen and have lower financial advisor quality metrics due to their infrequent participation in the bond market, the coefficients associated with both advisor quality measures are reduced for these models compared to the estimates in models (1) and (2).

Models (5) and (6) take only the subset of choices made by relatively high frequency issuers, those issuers with at least five issues during the 2004-2016 period. Local governments that have not issued bonds in the past 10 years will not have any measured state dependence that may influence their choice. Limiting the set of issuers to the local governments that participate more frequently in the bond market guarantees there will be some network connectivity between the local government and financial advisors in the bond market network that the local government may implicitly value. The results show a further reduction in the coefficients on the financial advisor quality measures, particularly for the experience-based measure of quality, suggesting that high-frequency issuers value measures of advisor quality relatively less than their previous connectivity to the financial advisor. However, for high frequency issuers, their assessment of relative financial advisor quality may be based on first-hand experience with the advisors rather than the more arm-length metrics of advisor quality used here.

None of the interaction terms between quality measures and issue size (in terms of issuer-normalized par value) display the expected relationship with choice. We expected that local government would be more likely to select high quality advisors when issuing larger bonds, but the opposite appears to be the case. This suggests state dependence is relatively more influential for larger issues compared to smaller issues. This possibly suggests some risk aversion on the local governments' behalf, returning to issuers that they have dealt with previously in order to avoind the risk associated with dealing with a new advisor. As issue complexity also increases with issue size, it could also be that the issuer expects the advisor to have learned from their previous issues and be better able to issue bonds with the issuer after working with them. This is the theory advanced in the literature that more stable networks may improve performance, but empirical evidence has not borne out this theory (Marlowe, 2007).

Like the coefficients on financial advisor quality, the coefficients on the state dependence measures are positive and statisticall significant for all models. However, interestingly, the coefficients on the financial advisor and indirect state dependence measures remain relatively unchanged across the alternative models. The underwriter state dependence measure is an exception which shows a marked decline when the advisor choice set becomes limited, likely because underwriters turned financial advisors are disproportionately represented in the advisors removed from the choice set.

The positive coefficients for both financial advisor quality and state dependence measures suggests issuers are making tradeoffs between using a financial advisor that they are connected to versus an advisor of higher quality. Because advisor quality is associated with lower true interest costs, this also implies local governments are trading off between using a financial advisor they are connected to versus lower expected interest costs. However, the actual effect of state dependence on expected true interest costs is ambiguous. Financial advisors that are more connected to local governments would also be more active in the bond market, leading to higher levels of quality. As such, the effect of state dependence on expected financial advisor quality, and, in turn, on expected interest costs, is unclear.

The estimated change in true interest costs as a function of state dependence, can be calculated as the change in expected advisor quality from setting the state dependence coefficients to zero for each choice compared to the actual estimate, and then multiplying this change by the coefficients associated with the linear regression of true interest costs on advisor quality. Formally,

$$E[\Delta TIC_{nt}] = \hat{\beta}_Q \times \left(\sum_j Q_{jt} \times \frac{e^{\hat{V}^Q_{jt}}}{\sum_{k \in K_m} e^{\hat{V}^Q_{kt}}} - \sum_j Q_{jt} \times \frac{e^{\hat{V}^Q_{jt} + \hat{V}^S_{njt}}}{\sum_{k \in K_m} e^{\hat{V}^Q_{kt} + \hat{V}^S_{nkt}}} \right) \tag{2.7}$$

Where $\hat{\beta}_Q$ represents the estimated relationship between advisor quality and true interest costs, Q_j represents the advisor quality measure associated with financial advisor j, and $\hat{V}^Q$ and $\hat{V}^S$ represent the estimated utility an issuer derives from financial advisor quality and state dependence measures, respectively.

Applying equation 2.7 using the estimate utility of choice comes from coefficients associated with model (2) in table 2.2, it is expected that state dependence leads to an experience quality factor score that is 0.45 points lower than it would be otherwise and a connectivity quality factor score that is 0.37 points lower on average. In all, the net expected effect on TIC using the estimated relationship between advisor quality and TIC from model (2) in table 1.4 is an increase in interest costs of around 2 basis points.

To see how contracting with additional financial advisors may increase expected advisor quality and thereby lower expected interest cost, we calculate the expected advisor quality for each choice where the issuer had previously used only a single financial advisor over the preceding ten-year period. This calculation is repeated for each choice instance where the issuer had previously used between two and five financial advisors over the preceding ten years. We then compare the expected true interest costs based on expected advisor quality for the issuers that had used more than one advisor to the expected true interest costs for issues where the advisor had only previously

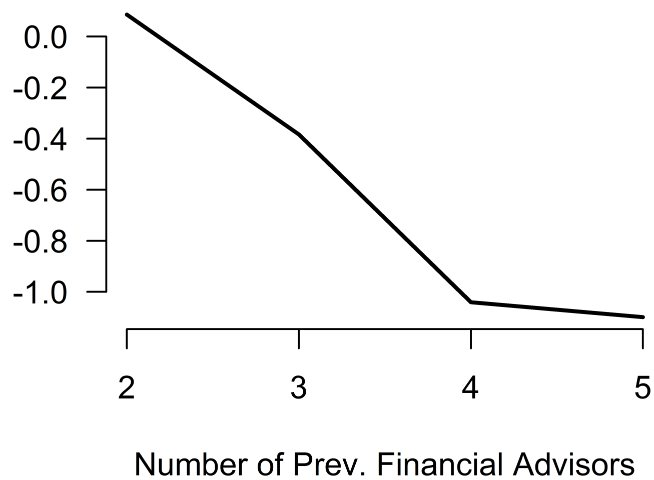


Figure 2.3: Expected difference in TIC basis points compared to an issuer that contracted with a single financial advisor (CA bonds only).

contracted with a single financial advisor. In order to avoid conflating changes in probability due to changes in size of the choice set, we limit this calculation to just California issues. The expected decrease in TIC due to change in expected advisor quality based on increasing the number of previous financial advisors is displayed in figure 2.3. Contracting with a second financial advisor does not provide any decrease in interest costs. However, three previous financial advisors is associated with an expected 0.4 basis point decrease in true interest cost, while 4 or more financial advisors is associated with a 1 basis point decrease in true interest cost

Finally, the choice decay measure is also relatively invariant across models at roughly 0.6. This suggests that the most recent connections between a local government and a financial advisor tend to be disproportionately influental in the current choice. For each subsequent choice, the influence of the previous choice is only 40% of their next most recent choice. For example, when a local government has issued six bonds, the influence of their first choice is just 1% of the influence of their most recent choice.

2.4.1 Sub-sample splits

Table 2.3 splits the sample according to whether a bond was a general obligation bond or a revenue bond. As noted above, it has been previously hypothesized that debt management network stability is more valuable for relatively complex issues (Marlowe, 2007).While this hypothesis has not yet found support in the empirical literature, if a financial advisor and local government have repeatedly interacted on bond issues, these interactions could result in mutual learning that leads to a better outcome for the issuer. In that case, we might expect state dependence to be greater for revenue bonds compared to general obligation bonds. State dependence represents a repeated interaction that could lead to learning. If the issuer recognizes this, there may be a tendency to choose a financial advisor that the issuer has interacted with more closely. In fact, the coefficients on the advisor state dependence measure are somewhat higher for revenue bonds compared to general obligation bonds, providing some weak support for the idea that issuers are more likely to use financial advisors they have a previous relationship with for more complex issues. Interestingly, the coefficients on the other two state dependent measures are lower for revenue bonds. In the case of the underwriter state dependence, it actually switches signs to become negative for some estimates. Cumulatively, these results suggest a strong preference on the part of local governments for working with a financial advisor with whom they have issued a bond previously rather than an advisor they are less directly connected with.

Negotiated and competitive bids are subject to separate conditional logit models in table 2.4. While somewhat less dramatic than the difference between general obligation and revenue bonds, bonds sold through a competitive bid process are somewhat less likely to use a previous financial advisor, but slightly more likely to use prior underwriter or indirectly-connected financial advisor compared to negotiated bonds. There is an element of reverse causality here. It could be that financial advisors that are repeatedly used tend to be more likely to sell a bond through negotiation rather than

Table 2.3: **Split-sample choice models of advisor choice (GO vs. Revenue bonds).** Multinomial logistic regression of choice of financial advisor for sub-samples splits containing only general obligation bonds or only revenue bonds as indicated in the table. Standard errors in parantheses.

	Dependent Variable: Chosen financial advisor			
	(1)	(2)	(3)	(4)
	(GO)	(Revenue)	(GO)	(Revenue)
Experience factor	0.401***	0.477***	0.145***	0.179***
	(0.009)	(0.010)	(0.014)	(0.016)
Connectivity factor	0.598***	0.361***	0.411***	0.118***
	(0.008)	(0.008)	(0.016)	(0.015)
Exp. factor × Par	0.009	−0.033***	0.006	−0.026**
	(0.009)	(0.009)	(0.011)	(0.011)
Conn. factor × Par	−0.020**	−0.031***	−0.037**	−0.098***
	(0.010)	(0.007)	(0.016)	(0.011)
Inactive Past Year	−2.493***	−1.672***	−1.761***	−1.114***
	(0.033)	(0.027)	(0.066)	(0.053)
State Dependence				
Advisor	4.655***	5.121***	4.515***	4.706***
	(0.017)	(0.024)	(0.021)	(0.031)
Underwriter	0.749***	0.069	0.140***	−0.099
	(0.041)	(0.073)	(0.052)	(0.072)
Indirect	1.656***	0.656***	2.037***	1.519***
	(0.058)	(0.079)	(0.085)	(0.107)
Choice Decay	0.649	0.607	0.621	0.587
δ	(0.037)	(0.036)	(0.039)	(0.040)
Choice Set	All	All	Top 20	Top 20
Issuers	All	All	Freq.	Freq.
Num. Choices	62,086	34,166	43,509	23,583
Adj. R^2	0.747	0.615	0.790	0.690

Note: *p<0.1; **p<0.05; ***p<0.01

a competitive bid. This potential for reverse causality is most directly evident in the coefficient associated with the network connectivity advisor quality measure. While it is possible that issuers who are selling a bond through a competitive bidding process may have a strong preference for using a highly connected financial advisor, it is perhaps more likely that a highly connected financial advisor is better able to gather more bids and therefore more likely to recommend a competitive bid sale. Perhaps even more likely, a financial advisor that tends to recommend competitive bids as a method of sale will tend to work with a broader array of underwriters, and therefore be better-connected in the bond network. In either case, this propensity would artificially bias toward zero the results of the regression of true interest costs on network connectivity-based financial advisor quality, as it does not account for the increased propensity to recommend a competitive bid sale which is associated with a reduction in true interest costs.

2.5 Conclusion

The choice model results shows strong evidence for considerable state dependence in their choice of financial advisor, reflecting a more general type of status quo bias. These results imply considerable implicit or explicit tendency in the bond market issue process to select a financial advisor that has been used previously, or one that is otherwise more closely connected to the issuer in the bond market more generally. However, this is mitigated by the fact that alternatives that are more likely to be chosen due to state dependence are also of relatively high quality. Nevertheless, there is evidence that state dependence has resulted in higher true interest costs for local government issuers than they would have otherwise achieved.

It is possible that being aware of this tendency and making it known and explicit will help municipalities avoid being state dependence in the future. However, an implicit piece of guidance

Table 2.4: **Split-sample choice models of advisor choice (Competitive-bid versus negotiated-bid issues).** Multinomial logistic regression of choice of financial advisor for sub-samples splits containing only competitively-bid issues or only negotiated issues as indicated on the table. Standard errors in parantheses.

	Dependent Variable: Chosen financial advisor			
	(1)	(2)	(3)	(4)
	(Competitive)	(Negotiated)	(Competitive)	(Negotiated)
Experience factor	0.470***	0.387***	0.207***	0.129***
	(0.010)	(0.009)	(0.016)	(0.014)
Connectivity factor	0.732***	0.349***	0.534***	0.090***
	(0.011)	(0.007)	(0.018)	(0.014)
Exp. factor × Par	0.020*	−0.027***	0.0004	−0.016*
	(0.012)	(0.008)	(0.014)	(0.009)
Conn. factor × Par	−0.028**	−0.022***	−0.037*	−0.081***
	(0.014)	(0.006)	(0.019)	(0.010)
Inactive Past Year	−2.306***	−1.913***	−1.568***	−1.279***
	(0.039)	(0.024)	(0.072)	(0.049)
State Dependence				
Advisor	4.657***	4.963***	4.563***	4.596***
	(0.021)	(0.019)	(0.025)	(0.025)
Underwriter	0.662***	0.383***	0.073	−0.031
	(0.046)	(0.057)	(0.057)	(0.063)
Indirect	1.216***	1.434***	1.812***	1.806***
	(0.067)	(0.064)	(0.095)	(0.093)
Choice Decay	0.626	0.637	0.592	0.621
	(0.041)	(0.034)	(0.041)	(0.039)
Choice Set	All	All	Top 20	Top 20
Issuers	All	All	Freq.	Freq.
Num. Choices	48,276	47,976	35,045	32,047
Adj. R^2	0.771	0.632	0.812	0.692

Note: *p<0.1; **p<0.05; ***p<0.01

for local governments based on these results is commensurate with the general finding in the government contracting literature that multiple independent sources of information tends to result in improved outcomes for the municipality (Brown & Potoski, 2003c; Girth et al., 2012). Even under state dependence, the wider the array of financial advisors and underwriters a local government has previously used will reduce the influence of state dependence on the issuer's choice and expand their local choice network. The positive relationship between advisor state-dependence and choice suggests that all else equal, local governments would benefit from contracting with multiple different financial advisors. And, the positive, though weaker, relationship between choice and indirect connectivity implies that contracting with financial advisors that are largely independent of each other in the bond network would further expand the range of possible financial advisors that a local government could contract with for relatively low transaction costs.

While we believe this research makes a valuable contribution in helping to illuminate local governments' contracting choices in the municipal bond market, we view this work as an intermediate step that suggests other possible contributions. Most importantly, while our empirical models suggest that expanding the implicit market for financial advisors may lower the transaction costs associated with choosing a high quality financial advisor and thereby lower interest costs, we do not explicitly model the link between prior choices and interest costs. We plan to extend this research to explore this link directly.

Our model has some limitations that may be explored in future literature. Other variables may also alter the probability that a local government will select a particular financial advisor. Political contributions may be a factor in early years, particularly. MSRB rule G-37 now prevents financial advisors from participating in issues with local governments if they have made a political contribution to an official within that government, but this rule was not in place for the entirety of our study period. More importantly, we do not observe any communication or connectivity outside of the bond network interactions. While this data is not available, it may still impact a local governments' choice of financial advisor. In particular, we do not observe government to government interactivity. We know information-sharing occurs at intergovernmental meetings, and information on advisor quality could well be disseminated via intergovernmental communication, but we do not observe this in our data.

Chapter 3

BROKERAGE AND TRADE IN ALASKA QUOTA-MANAGED FISHERIES

3.1 Introduction

Individual tradable fishing quotas and related catch share policies are a set of market-based fisheries management tools designed to reduce the inefficiencies associated with common pool resources. Under these policies, permission to fish an allotted amount in a given time frame is assigned as a property right that, while theoretically revokable, effectively endures in perpetuity. A key feature of this policy is that fishing rights are tradable among individuals, allowing quota owners to sell all or some proportion of their quota to another eligible person in the fishery. In theory, the assignment of transferable property rights will result in an efficient allocation of resources in the absence of appreciable transaction costs (Coase, 1960). The efficient transferability of quota is necessary for a market price for quota to emerge which then serves as a signal to harvesters to expand or contract their harvest operations in response to quota prices, leading to a more economically efficient harvest. The efficient transfer of quota and the emergence of a market price is therefore essential in the economically efficient harvesting of the resource (Newell et al., 2005; Squires et al., 1998). A single market price for quota can also be highly desirable in informing management decisions, particularly when accurate biological data is difficult to collect (Arnason, 1990; Batstone & Sharp, 2003).

Unlike other intermediate goods, which might require transportation costs to move the goods from the seller to the buyer and thereby incur direct costs associated with trading, quota shares are more akin to financial assets that exist on paper, and which may be transfered between buyers and sellers without any intervening costs other than the information costs that may be associated with trading. In the canonical model of quota trading in an efficient market, quota instantaneously converges to a single market price (Clark, 1980). Because quota is an intermediate good, the demand for quota among harvesters in the quota fishery is derived from their ability to generate revenue using quota. If the marginal profit of catch for a harvester is above (below) the market price for quota, the harvester will have an incentive to purchase (sell) quota, resulting in a single market price in the absence of search frictions (Clark, 1980).[1] The assumption of a single market price for quota has been empirically useful in estimating costs of quota restrictions (Kroetz et al., 2015), and the *in situ* value of fishery resources (Batstone & Sharp, 2003; Holland, 2013).

However, markets for fishing quota are decentralized, with no central hub to formally aggregate ask and bid prices from buyers and sellers such that the market clears at a single transparent market price. Transaction costs can emerge in these decentralized markets due to the implicit or explicit search and information costs that buyers and sellers must bear to identify prices, locate other potential market participants, and bargain over conditions of trade (Hahn & Stavins, 2011; Stavins, 1995). Theoretical models of pollution permit trading demonstrate how transaction costs can lead the allocation of property rights to diverge from market efficient outcomes (Fowlie & Perloff, 2013;

[1] To illustrate this more formally, we take the quota price model from Clark (1980) and the introduction of Ropicki & Larkin (2014). Harvester profit is commonly represented as $\pi_n = ph_n - c_n(h_n)$. On the revenue side, p represents the ex-vessel price for catch which is assumed to be common for all harvesters across the fishery, and h_n is the amount of fish landed by harvester n. On the cost side, $c_n(h_n)$ represents harvester-specific cost as a function of catch h_n. If the fishery is under quota policy with an efficient quota market, the harvester profit equation becomes $ph_n - c_n(h_n) - mq_n$, where m is the market price for quota and q_n represents the amount of quota held by harvester n. Assuming a binding total allowable catch, m will be positive and q_n will equal h_n because any unused quota does not generate any revenue. Quota market equilibrium is achieved at $\frac{\partial \pi_n}{\partial h_n} = p - \frac{\partial c_n}{\partial h_n} - m = 0$, and equilibrium is achieved when the quota price equals marginal profit for all harvesters.

Singh & Weninger, 2017).[2]

The diffusion of market information can be facilitated by social networks within the quota market. While this reduces the costs of gathering market information, and therefore reduces transaction costs of quota trading, information-gathering through social networks is uneven (Alatas et al., 2016). In particular, when seeking out trading partners, quota sellers may use their social network as one avenue to identify potential buyers, but which potential buyers are identified would be a function of how proximate the potential buyers are to the sellers in the social network. Sellers would have relatively low transaction costs of seeking out buyers close to them in the social network compared to those who are more distant.

In many quota fisheries as well as other rights-based management policies, brokers have filled the gaps in the social network and now conduct the majority of trades (Hahn & Stavins, 2011; Jin et al., 2019; Kroetz et al., 2015; Lee, 2012; Newell et al., 2005, 2007). Brokers in decentralized markets are considered 'market makers' in that they provide price information to market participants and identify trading partners in order to allow the market to function (Spulber, 1999). Broker services can be thought of as effectively expanding a seller's social network, allowing a seller to obtain additional market information and identify trading opportunities at a greater rate in exchange for a portion of the trade surplus (Duffie et al., 2005; Hendel et al., 2009; Salz, 2017). By identifying more trading opportunities, brokers would be expected to draw additional buyers from the upper tail of the distribution of willingness-to-pay in the presence of transaction costs in trading (Hong & Shum, 2006; Salz, 2017). This is also consistent with analytical models of 'internet gatekeepers'

[2]A related body of literature on the potential for a single large firm or group of firms to maintain an organized monopoly that strategically manipulates pollution permit prices at the expense of a competitive fringe of smaller firms originated with Hahn (1984) and has developed a substantial body of empirical and theoretical research (e.g. Dickson & MacKenzie, 2018; Hintermann, 2017; Montero, 2009; Wirl, 2009). While strategic trading in fishing quota markets has been the subject of scholarly attention as well (L. G. Anderson, 1991, 2008), it is less applicable to our particular context due to regulatory limits on quota aggregation which results in a large number of relatively small quota market participants.

(Baye & Morgan, 2001), where individuals can choose to interact with a disconnected local market, analogous to the seller's social network in our example, or an internet-based retailer that spans across local markets, much like the quota broker.

As of yet, the effect of brokerage services on trading behavior and price in fishery quota markets has been the subject to very little scholarly attention. In this paper, we use a confidential dataset of quota trading to explore two consequences of brokered trading in the Alaska halibut and sablefish quota markets. First, we test whether pairings of buyers and sellers are independent of other social network ties. In the absence of market frictions, we would not expect transactions to cluster within social network as that would imply transaction costs associated with trading (J. E. Anderson, 2011) leading to market inefficiency that a knowledgeable trader could exploit by selling between social network clusters (Jorion & Schwartz, 1986). Second, we test whether brokerage leads to a systematically higher sale price. Quota price is, at least in part, a function of the buyer's demand for quota. If sellers are able to get a higher price for quota sold through a broker, it would imply that non-brokered trades are on average being diverted to less efficient harvesters who have lower quota demand compared to harvester who purchase quota through brokered trades. As a consequence, the quota trading mechanism would be less effective in allocating quota to improve the economic efficiency of the fishery for non-brokered trades compared to brokered trades.

3.1.1 Previous literature

This research contributes to the developing literature on the micro-structure of quota market trading. While a robust economic literature has developed on the economic benefits of quota trading and other market-based solutions,[3] research on the structure of quota market trading is still rela-

[3]In many instances, catch share policies are replacing a system of season closures where a total allowable catch limit is set and the fishery closes for the season once that limit has been reached, leading to a 'race to fish' as

tively sparse, particularly with respect to brokerage activity and pairwise patterns of quota trading.[4] In an early network study of quota trading, van Putten et al. (2011) finds that well-connected shoreside processors have taken on a brokerage role in the market for rock lobster quota. They report two distinct parallel markets; the 'true market', which operates mainly through brokers with a well-known market price, and the 'social market' based on family and social relationships which may have lower prices. This roughly corresponds to our definition of method of sale, distinguishing between brokered and non-brokered quota trades, though we exclude any trade that is not arms-length. Modeling sale method in the sulfur dioxide allowance market using a random utility model, Sanin (2018) finds that private (non-brokered) trades tend to predominate in the market, but that trade between parties in different regional markets is conducted using brokers. Björk (2017) finds that some ITQ trades in Sweden are more likely if the traders share a social network relationship, such as low geographic distance or shared shoreside processors, but the econometric models do not account for the possibility of brokerage to mediate trade. With respect to the quota lease market in the British Columbia halibut fishery, Pinkerton & Edwards (2009) is particularly critical of the assumption that quota is traded on a single well-functioning market, and instead concludes that quota

operators catch as much fish as quickly as possible. Transitioning to catch shares is associated with numerous economic benefits, including longer fishing seasons by mitigating the race to fish (Birkenbach et al., 2017; Hsueh, 2017), increased fishery safety (Pfeiffer & Gratz, 2016), and increased ex-vessel prices for catch through improved product handling and changes in product form (Herrmann, 1996; Homans & Wilen, 2005). However, the ecological effects of catch share policies are mixed. Some research shows a positive effect (Costello et al., 2008), but others are less certain (Branch, 2009; Chu, 2009; Essington et al., 2012). Additional research on fishing quotas has noted the possibility for quota share programs to contribute to social disruption through the migration or consolidation of fishing rights (Carothers et al., 2010; Carothers, 2015; McCay et al., 1995; Ringer et al., 2018; Yandle & Dewees, 2008), as well as the emergence of production models that are perceived as inequitable or exploitative (Olson, 2011; Pinkerton & Edwards, 2009).

[4]The literature on brokerage in quota markets and other environmental permit markets largely concentrates on the promise of brokers to help markets function more efficiently. In a comprehensive overview of New Zealand ITQ markets, Newell et al. (2005) notes that brokerage use is common among a certain segment of the fishery, and further speculates that the decrease in price dispersion of quota price over time is partially attributable to brokers becoming established in the market and improving market function. In general, this agrees with other studies that conclude that the emergence of brokers leads to a well-functioning market (Hahn & Stavins, 2011; Stavins, 1998), or argue that the presence of brokers indicates an efficient market (Jin et al., 2019; Kroetz et al., 2015; Lee, 2012). By contrast, fishing quota markets with high brokerage fees and low brokerage use may be inefficient (Innes et al., 2014).

markets fail to achieve transparency leading to market power through information asymmetry.

Studies of quota prices are somewhat more common than trading behavior, but relatively few studies consider heterogeneity in market pricing for quota. Lee (2012) and Jin et al. (2019) use price data and buyer and seller characteristics to estimate market power in fishing rights trading markets in the Northeast groundfish and scallop fisheries, respectively, and find that more experienced buyers and sellers are able to get a better price, suggesting that market knowledge or experience can lead to traders capturing additional surplus from the trade. Similarly, Ropicki & Larkin (2014) find mixed evidence that a theoretically advantageous position in a social network leads to more advantageous prices, but they do find evidence of regional price dispersion, suggesting a segmented quota market. While the constructs that are being studied, such as experience and network position, would be the same advantages we would expect brokers to provide, none of the price models account for brokerage use. Studies of brokerage in the housing sector find that on average housing prices are not higher for sellers that use a broker, but they are sold more quickly (Bernheim & Meer, 2008; Hendel et al., 2009). Brokers may not achieve a higher price, but they are able to advertise the sale more effectively and gather more bids. Finally, Salz (2017) finds that buyers that use a broker to contract with private waste carter services in New York pay a lower price on average for carter services if brokerage fees are not taken into account, but a higher price when fees are considered.

3.2 Alaska Halibut and Sablefish IFQ Fisheries

The commercial halibut and sablefish fisheries in Alaska transitioned to an individual fishing quota policy in 1995. The subsistence, recreational, and for-hire guided angler halibut fishing sectors in Alaska are considered separate fisheries from the commercial sector and governed by a different process. While sablefish, also referred to as black cod, will occasionally be caught non-commercially in Alaska, it is rarely the primary target due to the typical sablefish water depth which is beyond the reach of recreational angling. Both fisheries restrict the commercial gear used to harvest halibut and sablefish to fixed gear only. Specifically, the use of trawl nets is prohibited in the halibut fishery, and using a trawl net is considered a prohibited species catch which cannot be retained by the harvester.

Before 1995, both fisheries operated on a system of seasonal closures. A total allowable catch limit would be set before each season and the season length was adjusted according to the length of time needed for that limit to be reached. While season length was roughly two months long when the policy began in the 1950s, the seasons had shortened to roughly 8 days long for sablefish and halibut seasons in some areas were less than 24 hours in the years leading up to the implementation of the IFQ policy. The result of this short season was a ‘derby’ fishery as harvesters competed against each other to catch as much as possible before the season ended, which has been shown to incentivize adverse economic decision-making including over-investment in factors of production (Stollery, 1986) and high levels of risk-taking (Wilen, 1979).

Catch shares were granted at the program’s inception in 1995 only to individuals who owned or leased vessels that landed catch in the commercial fishery in 1988, 1989, or 1990, and the number of catch shares each individual received was based on the best five years of their landings during the time period 1984-1990 for halibut and 1985-1990 for sablefish. The quota share represents a quasi-property right in that it represents a right to catch a certain proportion of the total allowable catch each fishing season, and this right can be given or sold to another individual who is eligible to receive quota.

3.2.1 IFQ Policy

IFQ areas

The halibut and sablefish IFQ policy assigns distinct classes of quota based on the location of the fishing activity and the type of vessel on which the fish is caught. The Alaskan halibut fishery is broken up into eight distinct management areas (figure 4.1). However, area 4E contains only community development quota, which is managed differently than the rest of the IFQ fisheries so it will not be covered here. Sablefish management areas are somewhat different but follow a similar spatial pattern, breaking up quota into Southeast Alaska, West Yakutat, Central Gulf, Western Gulf, Aleutian Islands and the Bering Sea (figure 3.2). A total allowable catch for both fisheries is set separately for each management area as a way of controlling the spatial distribution of catch. All quota shares are assigned to one of the management areas, and cannot be transferred between them, nor can quota assigned to one area be used to land catch from another area. The only exception to this is in areas 4C and 4D where the International Pacific Halibut commission sets total allowable catch combined for both areas, and quota assigned to 4C may be used to catch halibut in 4D since 2005.

IFQ vessel classes

Each quota also belongs to a particular vessel category (see figure 3.3), designed to preserve economic diversity in the methods by which halibut and sablefish are harvested. Vessels in category 'A' are catch-processors, meaning they process fish on-board the vessel before landing in a port. Other vessel categories represent catch vessels and are assigned by length: 'B' vessels can be any length while 'C' vessels are under 60 feet. Vessel class 'D' exists only in the halibut fishery, and

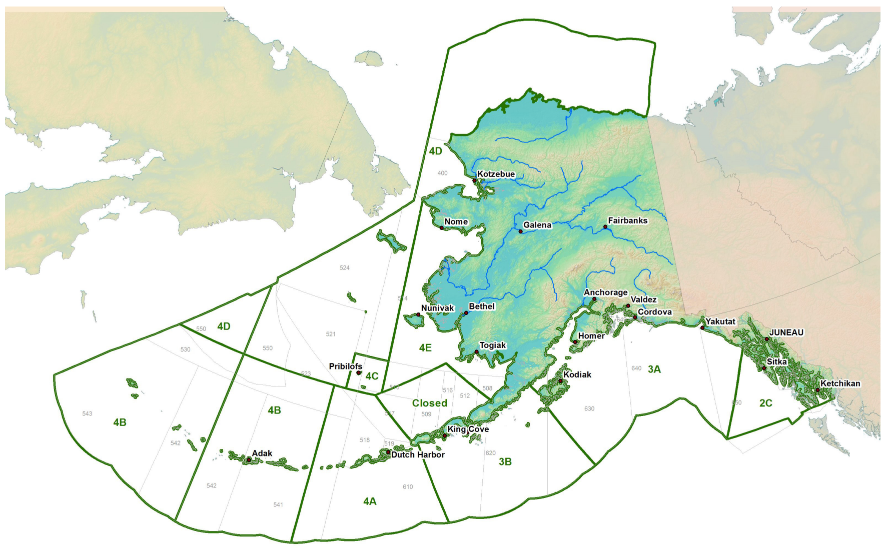


Figure 3.1: **Halibut Quota Management Areas** reprinted from (NOAA, 2019a)

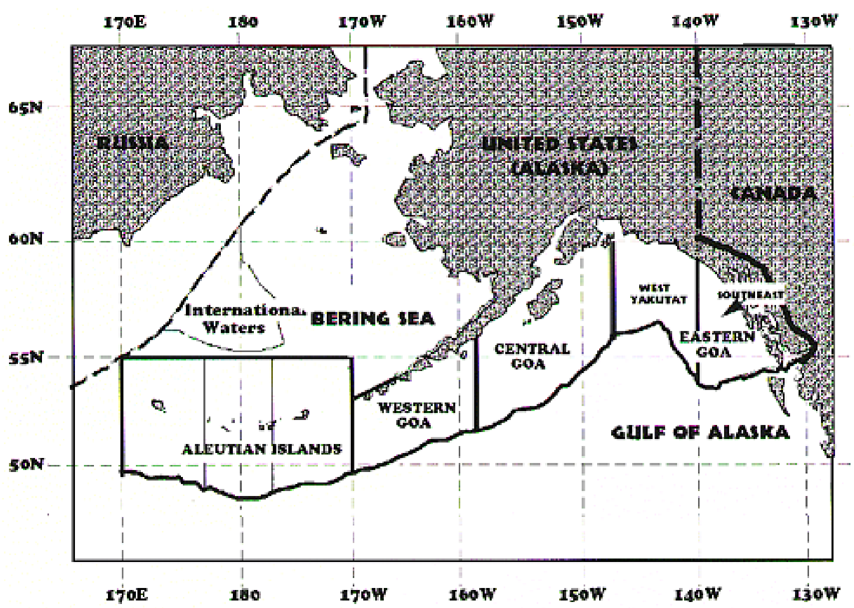


Figure 3.2: **Sablefish Quota Management Areas** reprinted from (Szymkowiak & Himes-Cornell, 2015)

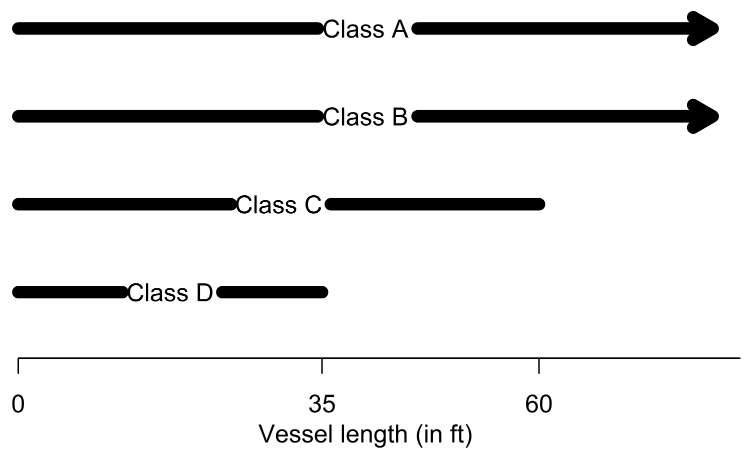


Figure 3.3: Halibut Vessel Category Size Restrictions. Sablefish is identical, but doesn't included a 'D' category.

are limited to vessels under 35 feet in length. Initially there were minimum size restrictions for the classes as well, but the North Pacific Fishery Management Council approved a "fish down" amendment in 1996 essentially eliminated the minimum size restrictions. Initially, less numerous Class B quota in halibut area 2C and the Southeast sablefish quota areas were exempted from the fish down amendment, though this exemption was removed in 2007. Further "fish up" amendments have been adopted as well, allowing Class D quota to be fished by vessels up to 60 feet in length in halibut areas 3B and 4C beginning in 2007 and 4B beginning in 2014. Despite the relaxations in vessel quota categories, quota use restrictions have effectively create a sub-market in quota for each vessel-area combination where prices for quota may move somewhat differently.

Quota blocking

Each quota share is either 'blocked' or 'unblocked'. If quota is blocked it must be sold as part of the same block, however smaller blocks may be 'swept-up' to form a larger block. Ownership limits in both fisheries initially limited individuals to owning two blocks or fewer, though this was amended to three blocks for the halibut fishery in 2007. Individuals may also purchase unblocked quota only if they own one block of quota or fewer in that fishery. Prices for blocked quota are somewhat lower than for unblocked quota (Kroetz et al., 2015). In general, when quoting prices, news organizations will report separate prices according to area, vessel class, and blocking, indicating a general recognition that prices for these rights can be somewhat different.

Quota rights and transfers

Most quota programs in the United States distinguish between two types of quota, and we follow the nomenclature established by Holland et al. (2015) and others in referring to them as "quota shares" and "quota pounds". Quota shares (QS) refers to the permanent right to catch a proportion of the total allowable catch, and which is carried forward year to year. Before the start of the fishing season, the fishery manager sets a total allowable catch (TAC), and each individual's quota shares are translated into the annual right to catch a particular weight of fish in the given fishing season and which expires at the end of the fishing season. This annual right is called "quota pounds" (QP), which are determined according to the formula $QP_i = TAC \times \frac{QS_i}{\sum_i QS_i}$ for each quota shareholder i.

In most quota fisheries, both quota shares and quota pounds can be transfered between eligible individuals. However, the Alaska halibut and sablefish quota fisheries have restrictions on quota pound transfers for catch vessel classes (classes B, C, and D). While quota pound transfers of up to 10% of an individual's quota were allowed in the first three years of the IFQ program in order for trading to become more regularized, there are significant restrictions that prevent quota pound sales except under particular circumstances. Due to the restrictions on quota pounds transfers and the lack of price information on quota pound transfers when they are permitted we focus exclusively on the quota share market.

A relevant exception to the general restriction on quota pounds trading is that quota pounds may be transfered together with the quota shares they are derived from. Roughly 78% of quota share trades in both halibut and sablefish fisheries include all of the quota pounds associated with the quota share, and we follow the quota brokers in referring to these quota shares as ‘unfished quota’. Quota shares may also be sold as having been ‘fished’ or ‘partially fished’, meaning that the trade includes no quota pounds or only a portion of the quota pounds associated with the traded quota shares, respectively, for the fishing season in which the trade takes place.

3.2.2 Quota brokers in the Alaska halibut and sablefish fisheries

Much like the real estate market, the Alaska halibut and sablefish quota trading market is driven by the decision of a quotaholder to sell, which creates the problem of how to locate potential buyers. Quota sellers report two main avenues to find a buyer: locating a buyer through their social network or through use of a quota broker. While there are other possible mechanisms through which to buy and sell quota, such as posting ads online or in newspapers, these other options are rarely reported. In the halibut and sablefish IFQ fisheries, brokers have been active in the market since the program’s inception. Even in the year 2000 fishing season among arms-length trades (which we define as trades where the buyer and seller do not report a prior relationship), nearly 75% of halibut quota sellers and 90% of sablefish quota sellers used a quota broker to locate a buyer (figure 3.4).

When selling quota through a quota broker, the broker will list the quota for sale, including the amount for sale, management area, vessel class, whether the quota is blocked, and whether the quota is fished or unfished in the current year. In early years of quota trading, brokers would

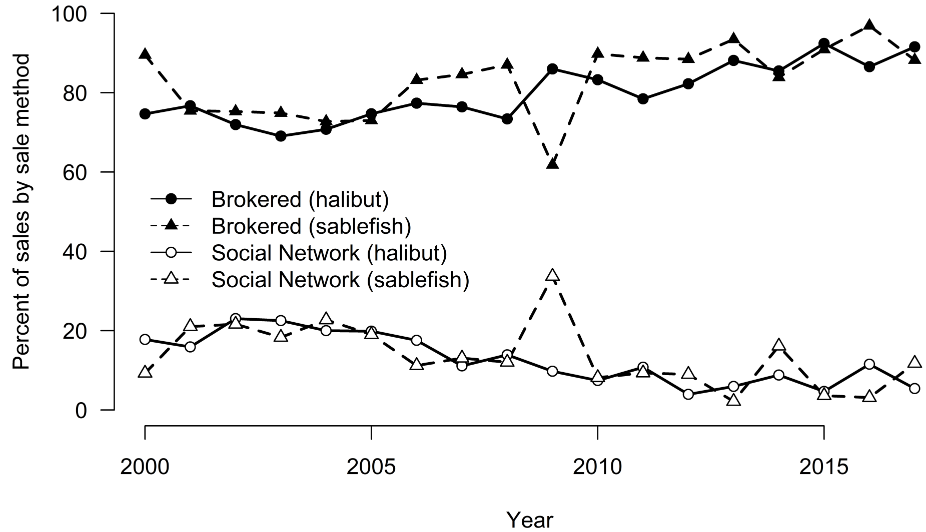


Figure 3.4: Quota share sale method in IFQ fisheries by year.

advertise quota for sale in trade magazines and newspapers, or print and distribute lists of quota for sale. However, since at least 1999, brokers have maintained websites which allows them to disseminate information more widely about quota that is on the market, and this is now the primary means of advertising quota for sale. Although brokers may also contact buyers who they know are in the market to buy quota based on previous communications or requests.

Example screenshots from brokerage websites are shown in figure 3.5, showing quota for sale on the market together with the ask price. Although the quota sold is quota shares rather than quota pounds, ask prices are given in terms of per-pound of quota shares at the current fishing season's ratio of shares to pounds of fish rather than in terms of a per-share price. Quota share prices reported in news outlets generally conform to this convention as well. Buyers are not obligated to pay the full ask price for the quota. Instead, if a buyer is interested in purchasing quota, the buyer and seller often negotiate over a price with the broker as an intermediary. Brokers typically also arrange escrow services and handle the administrative paperwork associated with the transfer.

HALIBUT

AREA	CLASS	B/U	POUNDS	PRICE
2C	C	B	700	64.00
2C	C	B	2,400	Make Offer
2C	D	B	850	50.00
3A	C	B	1,000	44.00
3A	C	B	1,100	38.00
3A	C	B	1,200	42.00
3A	C	B	1,800	40.00
3A	C	B	2,000	TRADE
3A	C	B	2,300	48.00
3A	C	B	2,600	42.00
3A	C	B	2,700	43.00
3A	C	B	3,100	42.00
3A	C	B	3,400	60.00
3A	C	B	3,800	45.00
3A	C	B	4,400	50.00
3A	C	B	4,600	50.00
3A	C	B	4,800	45.00
3A	C	B	5,200	60.00

Longline IFQs *[151 listings]*

ID	Type	Area	Class	B/U	Pounds	Asking
1566	Halibut	2C	B	U	150	$50.00
1574	Halibut	2C	C	U	39	$60.00
1556	Halibut	2C	C	B	750	$64.00
1493	Halibut	2C	C	B	400	$70.00
1506	Halibut	2C	C	B	3300	$60.00
1577	Halibut	2C	C	B	2700	$56.00
1555	Halibut	2C	C	B	2700	$67.00
1503	Halibut	2C	C	B	2600	$65.00
1606	Halibut	2C	C	B	2400	$66.00
1557	Halibut	2C	C	B	2000	$64.00
1504	Halibut	2C	C	B	1850	$65.00
1554	Halibut	2C	C	B	1800	$66.00
1457	Halibut	2C	C	B	1000	$68.00

Figure 3.5: Screenshots from websites of two quota brokers in IFQ fishery (*Alaska Boats and Permits IFQs*, n.d.; *Dock Street Brokers Longline IFQs*, n.d.)

Again like real estate brokers, quota brokers charge a fee equal to a proportion of the final sale price that is only collected if the fishing quota is sold. While this fee may vary slightly between brokers, in the Alaska halibut and sablefish fisheries the brokerage fee is usually about 3% of the total value of the quota sale. This is on the high end of the range of broker fees associated with the New Zealand fishing quota trading (Newell et al., 2005). It is also as great or greater than fees associated with pollution permit markets, such as U.S. sulfur dioxide permit trading market that arose from the Clean Air Act where brokers have charged 1% or less of the total trade value (Bailey, 1998), or the RECLAIM air pollution market in California where brokerage fees are likewise reported at 1-3% though buyers and sellers are also assessed additional administrative fees (Israels et al., 2002). However, it is less than the 8-15% brokerage fees reported in the Great Barrier Reef commercial quota fishery, which is characterized by high transaction costs (Innes et al., 2014).

3.3 Data and Methods

Comprehensive information on halibut quota transfers, permits, and landings are available for the years 2000-2017 through a confidential administrative dataset provided by AKFIN. While the IFQ program was implemented in 1995, reliable transfer data only extend back to the year 2000 fishing season. Each time a quota owner transfers quota to another person, they must complete a transfer application form that is submitted to NOAA fisheries for approval, and this information is recorded in a transfers database. Transfer information includes necessary information to complete the transfer, such as the transfer date, the IFQ area and species (halibut or sablefish), amount sold, and whether the transfer was a sale of quota shares or quota pounds. However, the transfer form also includes supplemental data that is of interest to social scientists wishing to study the quota trading system, such as reason for selling, how a buyer for the quota was located, relationship between buyer and seller, and sales price for the quota.

Information on annual quota holdings was also supplied in a different database that could be matched based on unique identifying numbers, which included annual city and state information, which allowed geocoding of each fishery participant at the city level.

Landings data is also provided by AKFIN, which includes identifying information for the quota owner as well as the individual who delivered the quota which may be different if the quota is fished by a hired master. Additional information includes species, the port where the landing occurred, pounds landed, the registered buyer associated with the landing, as well as the vessel's ADFG number.

Two key pieces of information are the identification of the individuals involved in the transfer of quota and the price that is paid. Given that the transfer form is used to assign quota, we can be reasonably confident that the buyer and seller information are accurately recorded. However, price information is voluntary provided and has no practical effect on the trading partners, possibly resulting in lower data quality.

To translate the transfer report price data to the single measure of quota share price, we begin by limiting the transfer dataset to quota share transfers that are not reported as being gifts, leaving 6,240 halibut and 2,609 sablefish non-gift quota share transfers.[5] Price information is recorded in the transfer form in three distinct places: traders may record a per-pound transfer price, a per-share transfer price, and/or a total price for the entire transfer. All three prices are present for more than 80% of observations, but only one or two listed prices also exist in the dataset for some transfers. We begin by translating all three measures into a common measure. 288 halibut and 158 sablefish transfers are removed that either do not report a price or report a low nominal price.[6] We further remove 374 halibut and 218 sablefish observations that report sales prices that contains discrepancies between the three different reported prices, though we retain 605 halibut and 390 sablefish observations that report three prices and only one of those prices is discrepant. We remove an additional two halibut prices that translate into more that $100 per pound of quota, and one sablefish price that translated into more than $50 per pound as likely representing data entry error as market prices for quota were well below those levels at the time of those respective sales. Finally, as reported in (Kroetz et al., 2015), the level of detail in the transfer data is sufficient to identify trades that may not be arms length, including transfers for which both parties are family,

[5]The AKFIN transfers database includes all quota transfers, including quota pounds transfers under special programs or policy exemptions, and beneficiary, administrative, and legal transfers. Because our focus is on the market for quota shares, we take as our starting place for data processing the set of all recorded quota share transfers that may be considered sales (i.e., the method of payment for the quota is not listed as 'gift').

[6]Despite not listing the transaction as a gift, 90 halibut and 30 sablefish transfers list a price as either zero or a small nominal amount such as $1 for the entire sale. It is unclear whether these trades represent gifts that were not listed as such in the transfer application or represent protest prices from traders who do not wish to record their transaction. Regardless, we treat any price of less than $0.01 per share as a missing price as that would be well below reasonable market value.

friends, or business partners. We remove these as the choice of trading partner as well as the price information may be skewed by the social relationship between the buyer and seller, resulting in 843 halibut transfers and 357 sablefish transfers removed from the dataset. This leaves 4,732 arms-length halibut transfers with valid prices and 1,876 arms-length sablefish transfers with valid prices which will be used as the transfer data for the subsequent analysis.

3.3.1 Social networks

To consider why transaction costs for some pairs of buyers and sellers may be lower than others, we can draw on previous social network analysis research. Quota trading relationships represent a particular form of social network, and social network analysis has been used to study the emergent properties of markets as well as other economic contexts (Jackson, 2010). A property that emerges across a variety of social network contexts is homophily, the tendency for social network relationships to form between actors that share particular traits in common, leading to clusters of more tightly-knit social networks within the larger social network graph (Goodreau et al., 2009). This tendency towards homophily exists in commercial fishing relationships. For instance, information-sharing about shark bycatch in the commercial tuna fishery has been found to cluster by ethnicity, with greater information-sharing within the same ethnicity than across ethnicities (Barnes et al., 2016). Homophilic social network ties often arise when an existing common trait between actors lowers the transaction cost barrier to forming other social network ties. Curtis & McConnell (2004) infer that harvesters that delivered catch to the same port are more likely to share information about fishing location choices. Bycatch risk pools, designed to reduce the risk associated with bycatch for individual harvesters, tend to emerge among harvesters that deliver their catch to the same shoreside processor (Holland & Jannot, 2012).

Social network measures

Transaction costs between each trading pair are captured across two broad measures representing social relationships - geographic distance and shared economic activity. Geographic distance is the most common variable included in gravity models of trade (J. E. Anderson, 2011), and geographic proximity has been shown to affect the probability of quota trading (Björk, 2017) and market price (Ropicki & Larkin, 2014). Actors who are more proximate are more likely to share friends or acquaintances in common through which trading information may diffuse. They would also be more likely to fish in similar locations given that travel distance is a ubiquitous factor in models of harvester spatial location choice. Quota brokers may also concentrate or specialize somewhat by geographic area. In other contexts, such as the housing market, brokers tend to have a limited geographic scope. While quota market products do not have nearly the same level of heterogeneity as housing markets, quota brokers may nevertheless specialize in trading to certain market areas, resulting in geographic clustering.

To construct geographic distance measures, we first create a dataset matching each quota market actor to their geographic location at the city level for each year by using the city and state information provided by AKFIN.[7] Raw geographic distances between cities are converted into two measures of geographic proximity. First, we transform the raw distance measure using the inverse hyperbolic sine (IHS) method. This is a method similar to transforming a variable using the natural log, and is recommended by Burbidge et al. (1988) when the dependent variable distribution includes both extreme and nonpositive values. As trades between buyers and sellers located in the

[7] In case of missing information for a particular year, we impute location information for the most proximate year for which AKFIN has valid geographic information and identify the geocodes for the city. We then use the application programming interface (API) for Google Maps to assign geocodes to each unique city in the dataset. A matrix of distances in kilometers between geocoded cities is constructed using the 'Haversine' method implemented in the geosphere package in R (Hijmans et al., 2019)

same city are present in the data, and would have a geographic distance of zero and therefore an undefined natural log, we use this method rather than logging the geographic distance to reduce the influence of extreme distance values. Second, we use a binary variable to indicate whether the buyer and seller reside in the same city, which we define as any distance between a buyer and seller that is less than 10 kilometers.

Shared economic activity is measured through the extent to which actors deliver their catch to the same shoreside processor and shared landing ports. Processors have driven the quota pound sales market in other fisheries (van Putten et al., 2011), and other relationships, such as risk-sharing networks (Holland & Jannot, 2012), have formed around shared shoreside buyers. Therefore, it is reasonable to expect that processors may play a coordinating role in quota trading. A binary variable is set equal to one if the buyer and seller in a quota trade delivered their landings to the same registered shoreside buyer. Information-sharing between harvesters may also occur while in port (Curtis & McConnell, 2004). We account for similarity in landing ports using the landings data provided by AKFIN using two measures. First, a binary variable is set equal to one if the buyer and seller in a quota trade landed catch at the same port. Second, we calculate the extent to which buyers and sellers distribute their catch similarly among fishing ports. We calculate a vector of landing weights at each port in a given fishing year, with separate vectors for both the buyer and the seller. We then calculate the similarity between these vectors using the cosine similarity method. The cosine method is similar to a Pearson correlation but is insensitive to zeros (Leydesdorff, 2005) and takes on a range of values $[0, 1]$ where 1 is perfect similarity and 0 represents no similarity between the two vectors (Huang, 2008). Because many trades occur prior to any fishing taking place, particularly by the seller, we use the shoreside processor sales and the port landings data from the fishing season prior to the season in which the sale takes place to define the shared processor and port relationship between buyers and sellers.

Table 3.1: Summary table of social network measures

Measure	Mean (Halibut)	Mean (Sablefish)	Definition
Same City	0.135	0.126	=1 if the trading pair lives within 10km of each other.
Distance	6.111	6.230	Inverse hyperbolic sine of geographic distance (in km) between buyer and seller.
Same Processor	0.131	0.163	=1 if the trading pair delivered to the same registered buyer during the previous fishing season.
Same Ports	0.226	0.295	=1 if the trading pair landed catch at the same port during the previous fishing season.
Similar Ports	0.141	0.155	Cosine similarity of distribution of trading pair's ports during the previous fishing season.

Social network methods

In a completely frictionless quota trading market, the underyling theory of bilateral trading models would suggest any seller would equitably distribute their quota among buyers (J. E. Anderson, 2011). However, equitable distribution of quota is unrealistic simply because quota is not easily divisible and division of some quota is prohibited due to fishery regulations. If it were divisible, even small transaction costs would add up if the seller were to attempt to separately transfer quota to many buyers. However, we can test whether there is evidence that transaction costs vary systematically among buyers and sellers in the quota market as a function of the social network measures defined in the previous section.

While small transaction costs may exist in a relatively efficient quota trading market, we would not expect these transaction costs to vary systematically among pairs of buyers and sellers. Adapting the implications of the gravity model to our purposes, the efficient market trading mechanism would imply that buyers and sellers are independent of each other. By that we mean that the probability of a buyer-seller pair engaging in a trade is conditional only on their individual propensity to buy and sell quota, respectively, and not on any dyadic attributes; i.e., for two otherwise identical buyers j and k who may have different relationships with seller i, $Pr(Y_{ijt}) = Pr(Y_{ikt})\ \forall j \neq k$, where Y_{ijt} equals 1 if actor i sells to actor j at time t and zero otherwise. Likewise, for two otherwise identical sellers i and l who may have different relationships with buyer j, $Pr(Y_{ijt}) = Pr(Y_{lkt})\ \forall i \neq l$. If buyer-seller independence holds it would not necessarily imply an efficient market without any appreciable transaction costs, but we could conclude that any transaction costs do not vary by trading partners and are therefore independent of the dyad, resulting in an integrated quota market.

To test the extent to which transaction costs differ among the buyer and seller dyads in the market we compare the observed social network measures defined above to the distribution of social network measures after accounting for individual level factors. Previous research on dyadic quota trading behavior has accounted for individual factors through individual-level fixed effects within a gravity model with quantity of quota traded as the dependent variable (Björk, 2017). However, due to the sparseness of trading in the halibut and sablefish quota share market, the majority of buyers and sellers would have zero trades in a given year, making standard linear models inappropriate without first accounting for the probability of trade.

Rather than using a parametric model of each dyadic value, we evaluate whether trade patterns are independent of buyers' and sellers' shared social networks by drawing on methods to evaluate the goodness of fit of exponential random graph models proposed by Hunter et al. (2008). Network model evaluation involves comparing observed test statistics to the distribution of test statistics generated by simulating the model many times over the given estimated network model parameters. To generate the distribution of test statistics under the assumption that trade is not affected by shared social networks between buyers and sellers we use a non-parametric random matching procedure. For each observed transfer in the data, we match a randomly selected buyer from the set of all quota transfers to a randomly selected seller from the set of all quota transfers. To control for all characteristics that may influence the individual propensity to buy or sell, the probability weight of drawing a given buyer or seller is equal to the number of purchases or sales, respectively, they engaged in over the study period within the same IFQ area and vessel class as the observed trade, with a weight of zero for any eligible quotaholder that did not buy or sell in that area and vessel class quota sub-market. We then save the relevant test statistics for the set of random draws over the whole dataset, which consists of the social network measures defined above, and the random draw is repeated $10,000$ times to generate a distribution of statistics. This is similar to the procedure outlined in Hunter et al. (2008) for simulating a network with a nodal factor effect for each node. Finally, we conduct another set of simulated draws by modifying the weights so that the random matching procedure disproportionately draws buyers and sellers who sold near the date of the observed trade.[8]

3.3.2 Quota price and method of sale

Quota for a particular area, vessel class, and species is completely standardized commodity in that a pound worth of quota can be used to catch a pound of that species within that area and vessel class regardless of other characteristics. However, due to the decentralized nature of the quota share market, there is not necessarily a single market price for quota share. In particular, quota share prices may diverge between the broker market and the non-brokered markets. Analytical models of search and brokerage have suggested that brokerage allows sellers to draw buyers from the upper tail of the distribution of willingness-to-pay (WTP) in the presence of transaction costs in trading (Salz, 2017), similar to analytical models of search behavior (Hong & Shum, 2006)

[8]The set of buyers and sellers are re-weighted according to the distance in time between when each buyer and seller was involved in a trade and the observed trade, weighted by a Gaussian kernel centered at the time of the observed trade with a 1-year standard deviation.

where brokerage is analogous to greater search capacity, leading to a higher price among brokered transactions compared to unbrokered transactions. Based on the model of quota share pricing, in the absence of capital constraints buyer WTP for quota equals the expected discounted future rents from the resource for the buyer which will be higher for more efficient harvesters. Jin et al. (2019) finds that a buyer's individual profit is positively related to quota prices, suggesting that more efficient harvesters are willing to pay more for quota. If brokers are able to locate buyers with higher WTP, and a significant proportion of quota is sold via some other means, this would suggest the trade mechanism is inefficient at redistributing quota to more efficient harvesters.

Ideally, we would estimate the difference in the average WTP among buyers that purchase quota shares via a broker and those that purchase them through some other (non-brokered) method. While we cannot observe buyer WTP directly, we can estimate the expected difference in price between selling quota using a broker compared to selling the same quota using non-brokered sale methods. Under a general bargaining model similar to those used in Harding et al. (2003) and adapted for quota trading by Jin et al. (2019), the sale of quota q at time t from seller i to buyer j could be represented as a bargaining solution that splits the surplus between the buyer and seller, $P_{qtij} = \alpha_{ij} WTP_{qtj} + (1-\alpha_{ij}) WTP_{qti}$, where $\alpha \in [0,1]$ represents the seller's relative bargaining power. If we assume in expectation that the buyers accessed through a social network (indexed by j') and those accessed through a broker (indexed by j) have the same expected bargaining power, then $E[\alpha_{ij}] = E[\alpha_{ij'}] = \alpha_i$, and the expected difference in WTP between buyer j and buyer j' becomes $\frac{1}{\alpha_i}(E[P_{qtj} - P_{qtj'}])$. Under these assumptions, the expected difference between brokered quota sale price and non-brokered quota sale price represents the minimum difference in willingness-to-pay between buyers accessed using the two methods of sale.

We model the expected difference in price between a brokered and non-brokered trade using the observed prices from trades at around the same time period to estimate the market price over time. While it is possible to estimate a structural model of quota share prices as a function of conditions in the halibut and sablefish market (Newell et al., 2005), structural factors, such as ex-vessel prices, catchability of fish, stock size, and costs of fuel and other inputs, tend to be correlated over time, suggesting that prices for quota shares that are transfered at approximately the same time will be facing a similar structural market. Rather than using market fundamentals as model inputs, we control for change in quota share prices over time, much like previous models of quota prices (Kroetz et al., 2015; Ropicki & Larkin, 2014). Newell et al. (2005) measures quota dispersion according to the average monthly quota price. Similarly, Kroetz et al. (2015) uses an annual fixed effect for each quota area to capture inter-seasonal market variations along with a single set of seasonal dummy variables to capture any intra-seasonal effects. Other methods for controlling for quota market price changes over time include nonparametric kernal smoothing (Kroetz et al., 2015) and high-order polynomials (Ropicki & Larkin, 2014). Each of these methods has their limitations. Annual fixed effects introduces an artificial discontinuity in the estimate at the border between years, which could cause some loss of intra-seasonal quota price changes. Certain quota characteristics may systematically affect prices, which kernel smoothing does not account for. Finally, due to the idiosyncratic timing of quota share trading and the sparseness of trades for some areas and times, a consistent time series cannot be generated from quota share prices posing challenges to using a high-order polynomial to smooth prices over time. Instead, we estimate quota share price changes over time using cubic b-splines. Each cubic b-spline is a set of piecewise third-order polynomials that creates a continuously twice-differentiable function, where pieces meet at pre-defined knots (Chib & Greenberg, 2010). We select a cubic specification for the basis functions due to its frequent use, smoothness, and relative parsimony (Chib & Greenberg, 2010; O'Sullivan et al., 1986), and we define the knots on an annual basis since that matches the frequency of management decisions, particularly catch limits.[9]

[9] In the appendix we present a comparison of models that control for quota share price over time using annual and

Despite the high degree of standardization of quota, there are two characteristics of quota that may have relevance to quota share sale price in addition to structural changes in the market. First, recall that quota shares on the market may be fished, unfished, or anything in between, so each transaction may include a different amount of quota pounds in the sale. Kroetz et al. (2015) deals with this issue by removing all trades from the dataset that are not unfished, leaving only trades for which all quota pounds associated with the share are included in the same quota share sale. While this includes the majority of trades, it leaves fewer observations to estimate the model parameters, and leads to less accurate estimates of market price.[10] Second, blocked quota is subject to more regulations than unblocked quota. Unlike unblocked quota, blocked quota cannot be divided up and sold to separate individuals, and there are limits to how many blocks an individual can own. Lower flexibility in blocked quota trading tends to lead to a lower price for blocked quota (Kroetz et al., 2015). We control for these two factors using fixed effects. In most model specifications, we also pool quota share prices across different vessel categories. In that case, we also include a fixed effect for each vessel category.

We estimate a series of models with the general form:

$$\ln P_{qt} = \delta Broker + R'_q \gamma_r + \gamma_m M_q + g(t) + \varepsilon_{qt} \tag{3.1}$$

Where *Broker* is equal to one if the quota sale was made through a broker, δ therefore represents the average increase in proportional price between brokered and non-brokered trades. The vector R represents the quota restrictions for each quota sale q, specifically, whether the quota is blocked as well as vessel category when the model is pooled across vessel categories, and M represents

seasonal fixed effects to models that use b-splines. The results suggest b-splines represent a marginal improvement for area-specific models, but the results are substantively identical for coefficients of interest.

[10] See the appendix for a comparison of model performance between estimates generated using unfished quota share trades only compared to estimates that incorporate price information from all trades.

the proportion of unfished quota share that is included in the trade. Finally, $g(t)$ represents the b-splines we use to estimate price changes over time. For any model that aggregates across IFQ areas, a separate b-spline is included for each area. ε_{qt} is the usual normal error term. We prefer a log-linear form in order to restrict expected prices to take on positive values, but the results are substantively identical.[11]

The choice of dependent variable deserves some mention here. As total allowable catch changes from year to year, the amount of fish represented by a single quota share will also change. We elect to match the common convention in the market by estimating quota share price P_{qt} in terms of price per pound of quota share during the year in which it is sold. A further rationale for our choice is that previous work has identified discontinuities in the per share quota share price that occurs in response to changes in the total allowable catch (Arnason, 1990; Batstone & Sharp, 2003). To translate the nominal reported price in the transaction data to real prices, we follow Ropicki & Larkin (2014) and index the nominal prices based on the Producer Price Index for Industrial Commodities using January 2017 as the base month.

3.4 Results

3.4.1 Quota trading and social networks

The distribution of social network statistics for buyers and sellers under the assumption of social network independence can be compared to the observed social network statistics for both brokered and non-brokered trades in both the halibut and sablefish quota share markets. If the observed mean is within the confidence interval defined by the simulated test statistics in the random matching

[11] See the appendix for a comparison of linear and log-linear model specifications.

procedure, we can conclude that trade patterns show evidence that market activity is independent of social networks.

The comparison of the average distance between buyers and sellers after the inverse hyperbolic sine transformation is shown in figure 3.6 for both halibut and sablefish quota share markets, separately. The observed transformed mean distance between buyers and sellers for brokered trades is nearly identical in the two fisheries, with averages of 6.47 and 6.46 for the halibut and sablefish quota markets, respectively. This translates into a distance of roughly 320 miles. These averages are considerably greater than average IHS of distance for non-brokered trades in both fisheries of 4.86 for halibut and 5.20 for the sablefish quota share market, or 65 miles and 91 miles, respectively. These results suggest brokers do in fact facilitate more distant trades. However, the buyer-seller distance for brokered trades in both quota markets is still below the lower-bound of the confidence interval associated with the simulated distributions. The expected average distance under weighted random matching is 394 miles for halibut and 403 miles for sablefish with a lower-bound of the 95% confidence interval of 371 miles for halibut and 364 miles for sablefish. Even among brokered trades buyers and sellers are less geographically distant than we would expect under truly random matching between trading partners.

Similar results can be found across the four other measures of social networks for both quota share markets, reported in figures 3.7 and 3.8. Again, we see that the observed average social network connectedness is greater for non-brokered trades than for brokered. For halibut, nearly 30% of non-brokered trades take place between buyers and sellers living in the same city, compared to just 9% of brokered trades. Similarly, compared to brokered trades, non-brokered trading partners are much more likely to deliver catch to the same processor, the same port, or similar ports. However, if brokers created a truly integrated market, we would expect the average social network measures for brokered trades to lie within the confidence interval representing random matching of buyers and

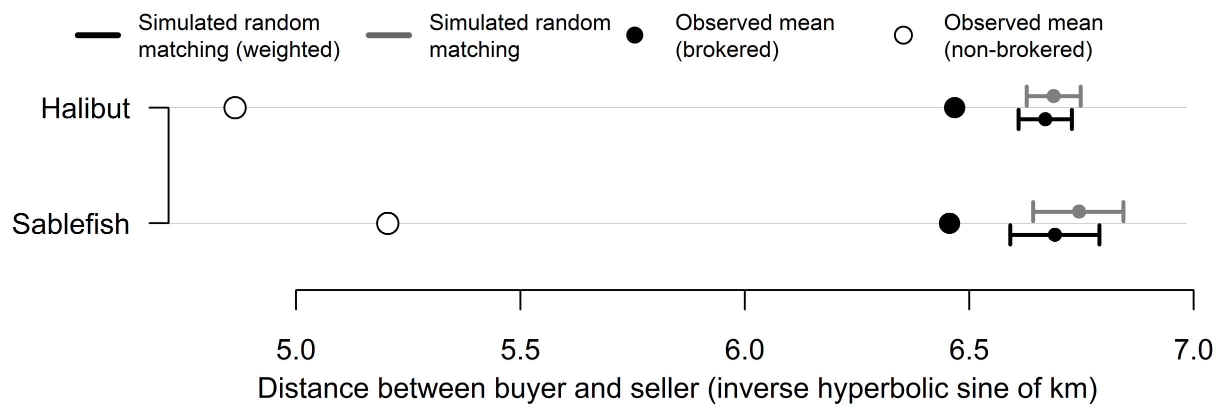


Figure 3.6: Social relationships between buyers and sellers for brokered and non-brokered fishing quota. The simulated distribution represents the 95% confidence interval for random matching across $10,000$ random buyer-seller pairings.

sellers. Instead, the social network measures for brokered trades are above the confidence interval, indicating greater social network connectedness than random matching would expect across all four social network measures. The same results hold true for sablefish trades. Although brokered trades are very close to the simulated random matching confidence intervals for some measures, brokered sablefish quota trades still demonstrate some social network dependence.

Patterns of brokered trades demonstrate considerably less social network dependence than non-brokered trades, suggesting lower transaction costs associated with trading. However, we still see some degree of social network dependence in the results for brokered trades. In practical terms, this social network dependence appears relatively small for brokered trades, but it persists across both geographic and economic social network ties, and across both fisheries. It is possible that this apparent social network dependence is an artifact from early trading years when communications technology and internet accessibility was far lower than more recent years.

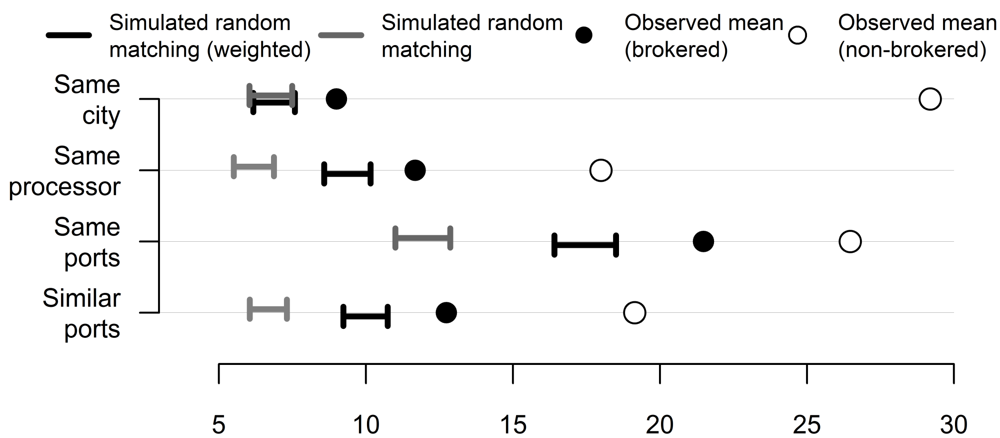


Figure 3.7: Social relationships between buyers and sellers for brokered and non-brokered in the halibut fishery. The simulated distribution represents the 95% confidence interval for random matching across $10,000$ random buyer-seller pairings.

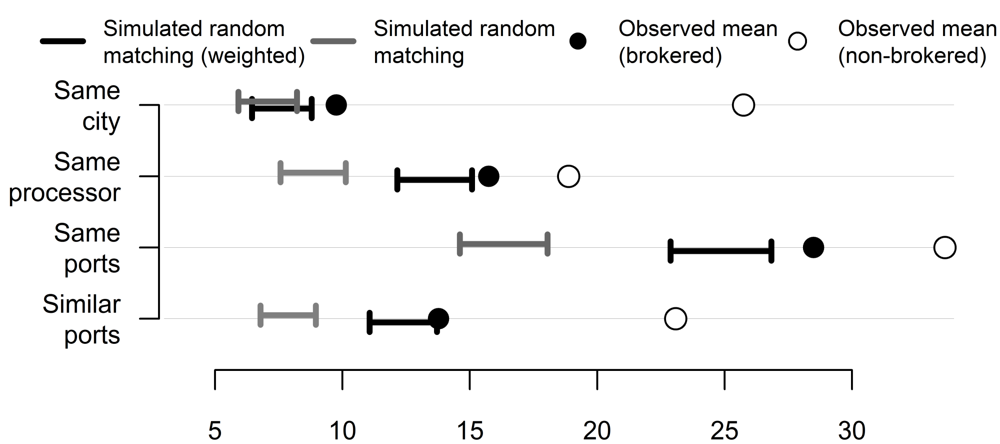


Figure 3.8: Social relationships between buyers and sellers for brokered and non-brokered in the sablefish fishery. The simulated distribution represents the 95% confidence interval for random matching across $10,000$ random buyer-seller pairings.

It is worth noting here that, unlike the geographic measures, the simulated confidence intervals for buyer and seller connectedness through ports and processors under random matching is greater for the weighted matching procedure compared to the un-weighted matching, indicating that the weighted matching procedure tends to match buyers and sellers that share social network connections. This is likely because the cities where buyers and sellers reside is relatively invariant over time. On the other hand, fishing activity including which port and processor catch is delivered to would change greatly over time as individuals alter their economic activity. Under the unweighted random matching procedure, a buyer and seller might be matched where one or both had stopped or started fishing or otherwise drastically altered their fishing practices by the time they actually purchased quota. For that reason, we prefer the weighted confidence interval procedure as well as the relatively stable geographic social network measures.

To test for this possibility that social network dependence has declined over time, we examine whether the probability that a buyer and seller reside in the same city and the probability that they deliver catch to the same port has changed for brokered trades over time compared to what we would expect under random matching. To do this, we create a smoothed mean over time for the observed proportion of brokered trades that occur between buyers and sellers that live in the same city. The estimate at each time period represents a local polynomial with a two-year bandwidth and a Epanechnikov kernel weighting and is conducted using the 'KernSmooth' package in R (Wand & Ripley, 2006). This procedure is repeated for each of the set of $10,000$ weighted randomly-matched trades, and a 95% confidence interval is taken for this simulated distribution at each point in time. We separately conduct this procedure for each fishery and repeat it for both social network measures.

The results presented in figures 3.9 and 3.10 do not show consistent evidence that brokered trades are becoming more independent of social network ties. It is true in all cases that by the last year of trading the observed mean for brokered trades has fallen within the simulated confidence interval for both measures across both fisheries. This may be taken as evidence that the most recent year of brokered trading does not show evidence that trade activity is connected to buyer-seller social networks. On the other hand, this does not appear to be a result of a consistent shift over time toward a more integrated market. Instead, there are fluctuations of the observed measures above and within the confidence interval for random matching. At various years, some quite early on, the observed smoothed mean lies within the confidence interval, and may deviate above the confidence interval for some time in later years.

Given that we do not see a consistent move toward an integrated brokerage market, we can speculate on possible explanations as to why some small influence of social networks appears to persist for brokered trades. There are at least five brokers active in the halibut and sablefish quota share markets that maintain websites with quota listings, and there may be others that have a lower online presence. For historical reasons, some segments of the market may preferentially use one broker over another. If buyers and sellers with shared economic or geographic characteristics are more likely to use the same broker, it may cause some small level of transaction costs to persist over time. Unfortunately, our data is limited to whether a broker was used to conduct the trade. It does not name the specific broker that was used. Even if it did, sellers may use multiple brokers to advertise a single trade, so it would be unclear the full list of brokers that were explored in the trade. It is also possible that some small social network dependence is not a universal feature of all brokerage, but rather that some brokers specialize on local sales while others have a broader reach to effectively integrate the quota share market. Ideally, a full roster of brokers and brokers used for each trade would allow us to perform a social network analysis, but this data is currently not collected for these fisheries.

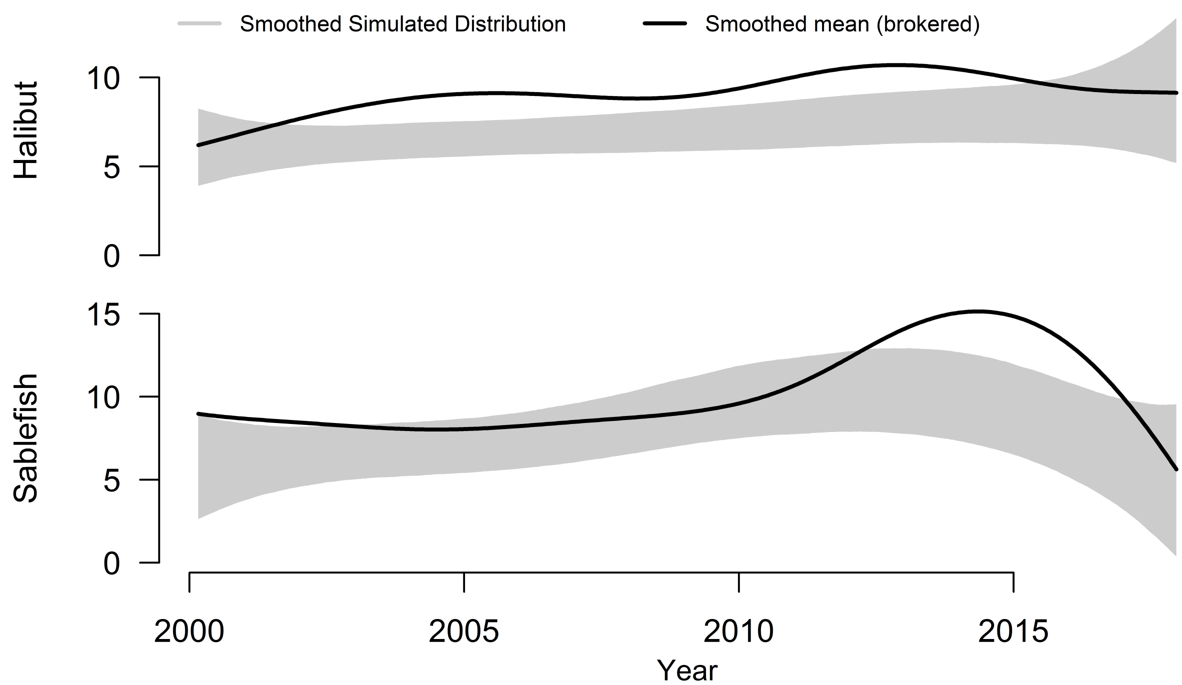


Figure 3.9: Smoothed percent of quota share trading partners that reside in the same city compared to the simulated smoothed average under weighted random matching. The simulated distribution represents the 95% confidence interval for random matching across $10,000$ smoothed averages where each smoothed average is based on a set of weighted random matches between buyers and sellers.

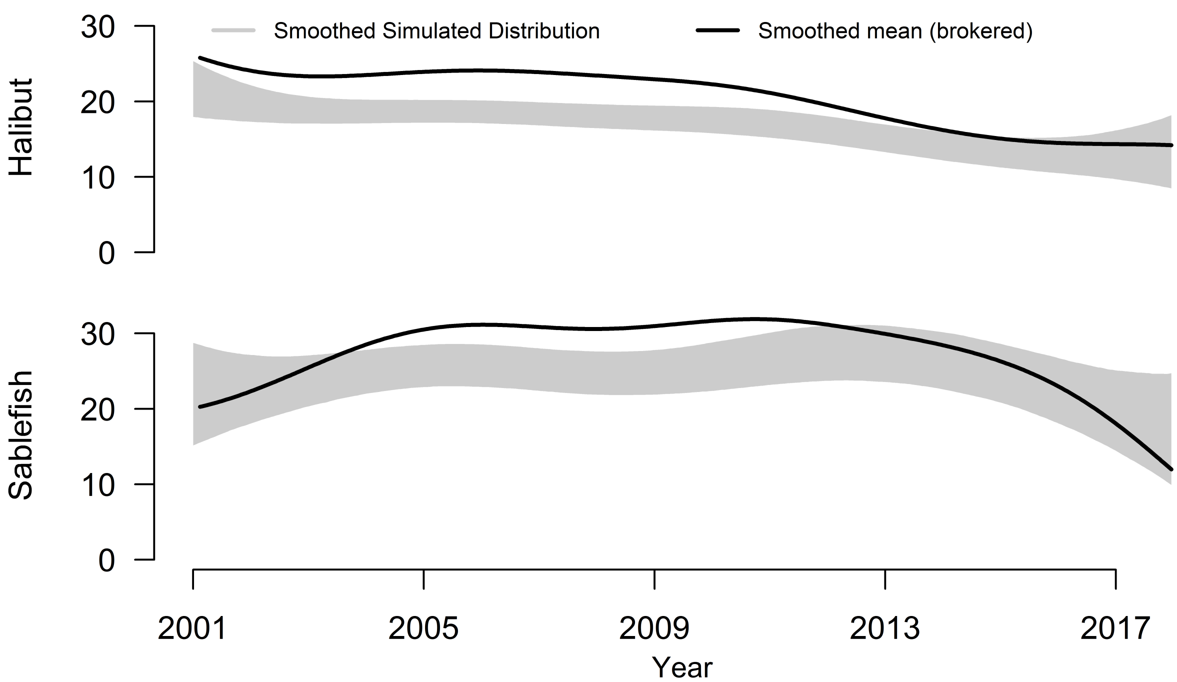


Figure 3.10: Smoothed percent of quota share trading partners that deliver catch to the same port compared to the simulated smoothed average under weighted random matching. The simulated distribution represents the 95% confidence interval for random matching across $10,000$ smoothed averages where each smoothed average is based on a set of weighted random matches between buyers and sellers.

3.4.2 Brokerage and Expected Prices

Turning our attention to quota prices, if brokers are successfully able to market quota to more efficient harvesters, we would expect brokered sales to enjoy a price premium compared to non-brokered sales. Estimates for models that pool across all IFQ areas as well as area-specific estimates for the relationship between brokerage and expected halibut and sablefish quota share prices are reported in tables 3.2 and 3.4, respectively. All estimates control for changes in the market over time using b-splines. In the pooled model, there is a distinct b-spline for each area. For the initial pooled and area-specific models of halibut price presented in the appendix, residual plots show large negative outliers for the estimated prices for each of the given model specifications despite our data processing procedures. Even though there is not a single market price for halibut quota shares, the approximate current market value should be broadly well-known given that brokers post ask prices on the website. Large deviations from this price are likely the result of data entry error. Non-monetary exchanges have also been reported in the market, where buyers and sellers may also trade other quota or even physical capital such as boats or equipment in partial exchange for quota and which is unreported in the transfer data. It is possible these large outliers are a result of one of these factors. We present an alternative specification for halibut with all data outliers greater than four standard deviations removed for each specification, which affects less than 1% of the data in the pooled estimates. For completeness, the untrimmed results are presented in the appendix while we present the trimmed results in the main body of the paper.

In the halibut fishery (table 3.2) we find that on average across IFQ areas brokered sale prices are just over 11% greater than non-brokered sale prices. This is consistent with most of the area-specific model specifications as the estimation results show brokered sale prices in areas 2C, 3A, and 4A to be 7.8% and 15.7% higher than non-brokered sale prices on average. These results are what we would expect if brokers were able to draw additional buyers from the upper tail of the distribution of willingness-to-pay for quota shares. The one exception to this is area 3B, where the estimated benefit of using a quota broker is only 3.9%, and is not statistically significant.

Table 3.2: Halibut quota share price (logged) model results with outliers removed for pooled and area-specific model specifications. Robust standard errors in parentheses.

	Dependent variable: Log of quota price per pound				
	All Areas	Area 2C	Area 3A	Area 3B	Area 4A
Brokered sale	0.112***	0.078***	0.157***	0.039	0.146***
	(0.009)	(0.014)	(0.015)	(0.027)	(0.026)
Blocked quota	−0.128***	−0.083***	−0.156***	−0.080***	−0.078***
	(0.007)	(0.014)	(0.011)	(0.020)	(0.024)
Quota pounds in sale	0.006***	0.017***	0.007***	0.004***	0.005***
(in thousands)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Vessel Category Controls:					
Class B	−0.151***	−0.184***	−0.143**	−0.106**	−0.214***
	(0.030)	(0.050)	(0.060)	(0.044)	(0.048)
Class C	−0.151***	−0.128***	−0.143**	−0.102**	−0.253***
	(0.030)	(0.043)	(0.059)	(0.045)	(0.051)
Class D	−0.341***	−0.311***	−0.321***	−0.295***	−0.434***
	(0.031)	(0.044)	(0.060)	(0.056)	(0.061)
Time Controls:	Area-specific cubic b-splines with annual knots				
Observations	4,706	1,356	2,063	573	367
Adjusted R^2	0.881	0.908	0.861	0.842	0.746
Note:					*p<0.1; **p<0.05; ***p<0.01

While both areas 3B and 4A have a lower sample size with larger standard errors, it is not clear why 3B would show such different price premiums for brokered trades than other IFQ areas. Part of this explanation could rely in the relatively low levels of fishing vessels under 60 feet in length.

In table 3.3 we present IFQ area and vessel-specific model estimates for vessel classes C and D in areas 2C and 3A, which are the area-vessel class combinations with the largest sample size. These results suggest the broker premium is lower for vessel class C than for D. Area 3B is dominated by class C vessels, suggesting that vessel length is one part of the explanation for lower brokerage premiums in area 3B. However, it is not clear why greater vessel length would result in lower brokerage premiums. Previous research in the housing market shows the absence of a brokerage premiums is made up for by more time on the market for non-brokered trades. It is possible that sellers who operate larger vessels may be more able to spend additional time looking for potential buyers than smaller vessel owners from class D, which would result in lower brokerage premiums overall. But, time on the market is not currently data that is collected as part of the quota transfer application.

In the sablefish fishery (table 3.4), we see that on average the brokerage premium is 3.2% and is not statistically significant. The area-specific models show similar results. In the Southeast and Central Gulf sablefish areas, brokerage premiums are estimated at 4.3% and 8.3%, respectively, though only the Southeast area brokerage premium is statistically significant. The results suggest that to the extent that a brokerage premium for sablefish quota share transactions exists, it is weaker than for halibut quota share trades. These are similar to the results we see in the area-specific model results for halibut area 3B. Similar to area 3B, the sablefish fishery does not include class 'D' vessels, possibly indicating that quota share owners who fish on larger vessels are able to take more time to sell their quota if they do not sell via a broker.

Table 3.3: Halibut quota share price (logged) model results with area-specific outliers removed for area/vessel-specific model specifications. Robust standard errors in parentheses.

	Dependent variable:			
	Log of quota price per pound			
	Area 2C		Area 3A	
	Class C	Class D	Class C	Class D
Brokered sale	0.064***	0.093***	0.078***	0.189***
	(0.013)	(0.021)	(0.012)	(0.021)
Blocked quota	−0.129***	−0.025	−0.184***	−0.098
	(0.012)	(0.081)	(0.011)	(0.064)
Quota pounds in sale (in thousands)	0.014***	0.038***	0.004***	0.037***
	(0.001)	(0.007)	(0.001)	(0.004)
Time Controls:	Cubic b-splines with annual knots			
Observations	730	519	1,024	704
Adjusted R^2	0.948	0.887	0.925	0.802
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 3.4: Sablefish quota share price (logged) model results for pooled and area-specific model specifications. Robust standard errors in parentheses.

	Dependent variable: Log of quota price per pound		
	All Areas	Southeast Area	Central Gulf Area
Brokered Sale	0.032	0.043^{**}	0.083
	(0.022)	(0.020)	(0.053)
Blocked Quota	-0.192^{***}	-0.157^{***}	-0.266^{***}
	(0.014)	(0.015)	(0.032)
Quota Pounds in Sale (in thousands)	0.002^{***}	0.005^{***}	0.003^{**}
	(0.001)	(0.001)	(0.001)
Vessel Category Controls:			
Class B	-0.240^{***}	-0.153^{***}	-0.118^{*}
	(0.027)	(0.031)	(0.064)
Class C	-0.273^{***}	-0.113^{***}	-0.141^{**}
	(0.026)	(0.025)	(0.057)
Time controls:	Area-specific cubic b-splines with annual knots		
Observations	1,876	581	508
Adjusted R^2	0.871	0.797	0.599
Note:			*p<0.1; **p<0.05; ***p<0.01

3.5 Discussion and Conclusion

The theory of quota trading in the absence of market frictions predicts convergence to a single market price for quota. However, a growing literature has studied how trading markets that develop for quota shares and other rights-based policy instruments match or diverge from theory to learn how such markets work in practice in the presence of various market frictions.

Our focus is particularly on the role brokers play in the market, which has been largely neglected in the quota literature. We examine two broad aspects of trading: trading patterns and prices. We find that non-brokered sales clearly fall along social network lines. Among other similarities, pairs of buyers and sellers in non-brokered trades are roughly four times as likely to reside in the same city as we would expect by chance. Brokered trades display some social network dependence, but overall this relationship is much smaller than for non-brokered trades and might not have much practical significance. This suggests brokers are largely successful in integrating the quota share markets for both halibut and sablefish, though some small level of residual social network clustering still remains. A relatively small degree of residual social clustering appears relatively stable over time, and has not consistently diminished even as the internet and other technology have reduced the cost of communicating market information.

We also find that quota share prices are expected to be higher for brokered sales than for non-brokered sales. The sign on this relationship is consistent across species and IFQ areas, although it is not always statistically significant, particularly where there are fewer smaller fishing vessels. If brokers are able to achieve a higher price for quota, this suggests they are able to access segments of buyers that have a higher willingness to pay, and may therefore be more economically efficient. One alternative explanation for higher prices for brokered sales is that the emotional distance afforded by anonymizing the trade through a broker could allow the seller to avoid guilt in pursuing the highest possible price (van Putten & Gardner, 2010). While we have tried to take this possibility into account by removing all trades where a relationship between buyer and seller was reported prior to the trade, it is still possible there is still some unwillingness of the seller to pursue the highest price possible in a face-to-face trade. However, it is not clear why this would affect only the seller and not affect the buyer in a symmetrical way.

There are several shortcomings of the data that prevent us from completely exploring quota share market function. First, price data is voluntarily reported and may be inaccurate or incomplete, particularly if any barter was included as part of the transaction. We have attempted to take this into account through data processing and outlier-trimming, but there is no way to tell how accurate the price data is. Second, the brokers used for the sale are not listed in the transaction. Nor do we have a full roster of social contacts for each quota market participant. This prevents us from conducting a full social network analysis of the quota share market, requiring us to aggregate all brokered sales under a single method of sale, and to approximate social network ties through other measures. Third, unlike other research examining brokerage in the housing market, time on the market is not included in the quota share transaction data. As a result, we cannot know to what extent sellers trade-off price and speed of sale.

An important aspect of the halibut and sablefish quota share policy that we do not explore in depth but would be valuable for future research is the growing role of quota pounds transfers in addition to quota shares. There are restrictions to transfering quota pounds, but an exception to this policy was granted in 2007 to allow quota pounds to be sold for medical reasons if certain conditions are met. This has quickly increased the volume of quota pound sales so that as of the 2017 season the quota pound market was roughly as large as the quota share market. However, the quota pound market was largely conducted without brokered sales. It is unclear why quota pounds were not sold via brokers. It is possible that because quota pounds are only worth roughly 10% of what quota shares are worth, it might not have been sufficiently valuable for brokers to advertise it. Transfer records suggest the quota pounds are sold in return for a portion of the gross revenue rather than for a set price, which might also complicate brokerage arrangements. Whatever the cause, based on our results the lack of brokerage for quota pound transfers would be expected to result in a disconnected market, while also possibly diverting the quota to less efficient producers. This echoes some of the critiques of the quota pound market for halibut in British Columbia (Pinkerton & Edwards, 2009).

Future research may also develop a more structural approach to both willingness to pay for quota share as well as observed quota price. We control for changes to the market over time without addressing the underlying market forces that may shape willingness-to-pay for quota. This data is not available as consistently as quota share transfer data. But, estimating quota share prices as a function of ex-vessel landings prices, input costs, and possibly expectations of future profitability would be a valuable contribution. Similarly, while we observe quota share prices, the underlying willingness-to-pay for quota is unclear. In theory, the willingness-to-pay reflects the shadow value of the resource, and can therefore be a valuable way to evaluate changes in policy, particularly how changes to policy may have heterogeneous impacts among groups who may otherwise be vulnerable or marginalized in the fishery. We leave both of these to future work.

A key conclusion of our research for any fishery contemplating implementation of a quota share policy is that brokers are key in integrating the market. Widespread brokerage use is then a key aspect in developing a market that achieves the policy aims of economic efficiency. An aspect of the market that we do not explore here is the decision to use a broker. Brokerage fees may deter some sellers from using a broker to sell their quota, which may reduce the economic efficiency of the quota market. The fees themselves are not welfare-reducing as they represent a transfer drawn from the surplus derived from the trade. So long as fees are sufficiently low that they would be unlikely to dissuade a seller from participating in the market, the fees have no affect on welfare

Hendel et al. (2009); Newell et al. (2005). In the halibut and sablefish fisheries, fees of roughly 3% of the sale are sufficiently low that brokerage is widespread and probably would not prevent anyone from selling their quota. However, if fees are sufficiently large to reduce market activity, this would negatively affect welfare.

Even if brokerage fees do not affect market participation, they could reduce the likelihood of selling via a broker, which could negatively impact the quota market. If brokerage fees are high and relatively few trades are conducted via a broker as a result, it is unlikely that the quota market can be integrated with a transparent market price. Costs and efficacy of brokerage may vary considerably between fisheries. Any fishery contemplating switching to a quota share policy should analyze the capacity of other actors in the market to serve as brokers. In the halibut and sablefish markets, this role has been filled by actors, generally former harvesters themselves, who also serve as brokers for other markets, such as capital equipment and other fishing permits. In other rights-based fisheries, shoreside processors have taken this role instead by coordinating trades and providing other information to the harvesters that they purchase from. Accounting for method of sale and the ways in which different policy or ecological contexts may affect method of sale and, in turn, affect the functioning of the quota market are necessary to the successful implementation of rights-based policies.

Chapter 4

ESTIMATING WILLINGNESS-TO-PAY FOR FISHING QUOTA USING A RANDOM BIDDING MODEL

4.1 Introduction

Empirical models of quota share price often assume a single willingness-to-pay for quota at the margin by assuming a well-functioning market that has converged on a single quota price. This assumption of a single market price follows analytical models developed by (Clark, 1980) among many others to demonstrate how the market price for quota reaches a single price which equals both the shadow price of the resource *in situ* as well as the marginal profit of quota across each participant in the fishery. A more detailed review of this model is presented in the previous chapter. The assumption that an efficient market produces a single market price is used in many analyses of quota trading to estimate dynamic response to changes in policy (Batstone & Sharp, 2003), the costs associated with trade restrictions (Kroetz et al., 2015) as well as the relationship between quota pound price and quota share price (Jin et al., 2019; Newell et al., 2005, 2007).

However, price dispersion in quota markets, including the Alaska halibut quota share markets, implies a distribution of willingness-to-pay for quota shares among fishery participants. Particularly in response to policy, it can be valuable to estimate the distribution of willingness-to-pay, particularly when evaluating a change in policy that may have distributional consequences. In this paper, we develop a model of willingness-to-pay for quota based on an auction model of quota sales, and apply this model to the halibut Alaska IFQ fishery to estimate how willingness-to-pay for quota varies across Alaskan communities. We then evaluate how a policy to allow limited transfers of quota from the commercial fishery to the recreational fishery differentially affected willingness-to-pay for commercial quota.

4.1.1 Previous literature

Focused on the housing market, Harding et al. (2003) suggests price dispersion may derive from market thinness caused by the large degree of heterogeneity of the underlying housing products. Within thin markets, asymmetric bargaining power as well as a heterogeneous distribution of demand for housing characteristics among buyers and sellers in the market produce systematic price dispersion even after accounting for the value of housing characteristics. They suggest a linear model of housing prices as a function of housing characteristics and buyer and seller characteristics that may affect housing demand or bargaining power. By assuming symmetric bargaining power and demand between buyers and sellers, systematic differences in both bargaining power and demand among housing market participants can be identified.

While individual fishing quota and other individual access rights such as days-at-sea permits, are largely homogeneous goods, the relatively few number of buyers and sellers in many quota markets suggests a similar empirical bargaining approach based on the assumption of a thin market might be appropriate. Lee (2012) adapted the model from Harding et al. (2003) to estimate bargaining power in the market for tradable days-at-sea allowances in the Northeast U.S. groundfish fishery based on vessel characteristics. Jin et al. (2019) uses a similar model to estimate how quota lease prices in the scallop fishery diverge based on buyer and seller characteristics. In particular, they find that quota lease price is positively related to the fishing profit of the buyer, negatively related to the buyer's allocation and seller's market experience, and varies by buyer and seller region. Together this suggests that economic productivity increases demand, leading to a higher willingness-to-pay, and that quota traders with more market experience and more assets are able to receive more advantageous prices. Ropicki & Larkin (2014) use a similar approach to estimate a linear model of quota lease price as a function of buyer and seller network attributes. In general, they find some evidence of systematic price dispersion, particularly that sellers who are better-connected in the lease network (i.e., those that have sold quota to a greater number and to more diverse individuals) are able to attain a higher price for their quota.

An important limitation of Harding et al. (2003) and similar approaches is that they treat the seller-buyer pair as if it were fixed. Rather than a matching process for the trading pair, the model assumes a trade between the observed buyer and seller and, within that trade, the buyer and seller bargain to reach an equilibrium price. However, as we reported in the preceding chapter, fishing quota may be sold through a quota broker who will help to advertise the quota to potential buyers, allowing sellers to collect multiple bids. Similar brokerage systems have been reported for many quota share markets (Jin et al., 2019; Kroetz et al., 2015; Lee, 2012; Newell et al., 2005; Innes et al., 2014) as well as for transferable pollution permits (Hahn & Stavins, 2011; Stavins, 1998).

4.2 Random Bidding Model

4.2.1 Background and model overview

Rather than a linear model of prices as has been done previously in the literature, we model the quota selling process by adapting the random bidding model (Ellickson, 1981) and its extensions (Lerman & Kern, 1983) of quota sales as an auction within a latent choice set framework. This requires us to make the assumption that sellers are profit-maximizing, selling their quota to the highest bidder. As the Alaska halibut IFQ fishery we apply this method to later is a commercial fishery, profit-maximization appears to be a reasonable assumption[1] and one that is common in the literature on fishing quota markets (Jin et al., 2019; Newell et al., 2007) as well as other behavior such as choice of a fishing location (Haynie & Layton, 2010). Potential buyers bid according to their willingness-to-pay for quota, as in the original random bidding model proposed by Ellickson (1981) and similar 'bid-rent' models that model real estate prices as auction outcomes (Martínez & Henríquez, 2007; Muto, 2006).

Profit-maximization implies that the benefit a quota seller derives from using a broker to conduct a sale is through a higher final sale price for the quota rather than because selling quota through a broker confers some intrinsic benefit. This differs from previous research on the sale of SO_2 permits as part of the U.S. acid rain program, which modeled the choice of sale through a broker or professional market maker as a random utility model (Sanin, 2018). In the Sanin (2018) model, the firm receives some utility benefit from engaging in a particular method of sale. Our dataset is advantageous in that it contains price information as well as method of sale, allowing us to focus directly on profit-maximization from the sale rather than utility maximization associated with selling to a particular individual or by a specific method of sale. Instead, we follow previous work on market intermediation in assuming the benefit from using a broker derives from increasing the number of buyers a seller is able to market their quota to (Hong & Shum, 2006; Salz, 2017). This increase in exposure from advertising quota through a broker should lead to additional bids, particularly from buyers with higher willingness to pay for quota, thereby increasing the quota sale price on average as the quota is sold to the highest bidder. As the seller's cost of using a broker is

[1] 23% of halibut transfers are listed as gifts, usually to family members. While this implies the existence of some transfer considerations that are not purely monetary, prior research suggests that some of these gift transfers are to avoid individual quota aggregation limits by nominally transfering the quota while allowing the original quotaholder to retain effective control. Regardless, from a modeling perspective among trades that report prices the assumption of economic maximization within the fishery appears to be a reasonable starting point.

zero until or unless quota is sold through the broker, we assume that sellers gather bids through the broker as well as other means (such as informally through their social network) for a set period of time. After this period of time, they sell their quota to the bidder that will generate the greatest sale value for the seller. Because broker's charge a fee for their services, the bidder that generates the greatest sale value is not necessarily the bidder with the highest bid. Instead, the seller discounts bids generated through the broker by some rate (denoted τ), which is assumed to be equal to about 3% given the prevailing brokerage fees for the halibut quota markets.

4.2.2 Model formulation

The model is formulated by assuming that each bidder belongs to a distinct category. When considering potential distributional consequences of a quota policy, it is often valuable to focus on distinctions between fishing participants based on community characteristics such as size (Carothers et al., 2010), fisheries portfolio diversification (Cline et al., 2017) or intensity of fishing involvement (Himes-Cornell & Kasperski, 2016). Any of the individuals within a category, indexed by $k \in K$, can bid for quota, and do so at their willingness-to-pay. A member i of bidder category k's willingness-to-pay for quota sale q at time t is denoted by wtp_{iqkt}, and varies systematically across groups through an observed component (ψ_{qkt}) but also has a random component (ε_{qikt}) for each quota sale:

$$wtp_{qikt} = \psi_{qkt} + \varepsilon_{qikt}. \tag{4.1}$$

Where the random component is assumed to be idependentally and identically distributed (iid) with generalized extreme value I distribution (also called a Gumbel distribution, denoted GEV1 below), for each individual, with a location parameter of zero and a scale parameter of σ.

As the sale goes to the highest bidder, a buyer from category k purchases the quota if and only if the observed component plus the maximum of the random component for the buyer's category (k^*) exceeds the observed component plus the maximum of the random component for all other (non-buyer) bidder types (k):

$$\max\{\psi_{qik^*t} + \varepsilon_{qik^*t}\} > \max\{\psi_{qikt} + \varepsilon_{qikt}\} \forall k \neq k^*. \tag{4.2}$$

The assumption that ε_{qikt} has a type-1 extreme value distribution allows us to take advantage of the useful property that the distribution of the maximum of any number of draws from the distribution is itself a type-1 extreme value distribution with a scale equal to the scale of the original distribution and a location parameter equal to the scale multiplied by the natural log of the number of draws. That is, $\max \varepsilon_{qikt} \overset{iid}{\sim} GEV1(\sigma \ln(M_{qkt}), \sigma)$, where M_{kqt} represents the number buyers in category k bidding on sale q at time t. Consequently, the expected value of $\max\{\varepsilon_{qikt}\}$ is $\sigma \times (\ln(M_{qkt}) + \Gamma'(1))$, where $\Gamma'(1)$ is the first derivative of the gamma function evaluated at one and which equals the Euler-Mascheroni constant with the approximate value of 0.57721.[2]

Because the seller can sell using a broker or through non-brokered means, any sale that uses a broker confers greater benefit to the seller than any of the non-brokered sales that might be available for that particular sale instance. The reverse is also true, if a seller does not use a broker, we assume here it is because that gives the seller the highest net sale value for their quota. As brokered trades are anonymized, potential buyers may bid using either sale mechanism. We assume brokerage affects the bid value through the number of bids the seller receives, rather than the underlying

[2]This formulation differs from Lerman & Kern (1983), which assumed an error term ε_{qikt} with a scale parameter equal to one. See the appendix for the calculation of the expected maximum value of the error when the scale parameter is freely estimated.

willingness to pay for each group. Any systematic difference in price and choice of method of sale is attributable to differences in the mean of random component ε through the gathering of different numbers of bids. Rewriting the model to incorporate method of sale and ignoring the brokerage fee for now and suppressing the time index, the seller sells to bidder type k^* using sale method s^* if:

$$\psi_{k^*} + \sigma \ln(M_{qs^*k^*}) + \varepsilon_{qs^*k^*} > \psi_k + \sigma \ln(M_{qsk}) + \varepsilon_{qsk} \; \forall \; \{k,s\} \neq \{k^*,s^*\}. \tag{4.3}$$

Where $s \in \{\text{broker, nonbroker}\}$ denotes the two methods of sale. So, any observed sale method and bid type will be chosen if the willingness-to-pay of bidder of type k^* collected through method of sale s^* exceeds all bids from other bidder types $k \neq k^*$ for method of sale s^* as well as all bids collected via the method of sale that was not chosen.

Unlike the more common multinomial regression discrete choice model where the choice is observed but the numerical value of the choice is not, we can use price information to exactly identify the scale of the random error term ε (Lerman & Kern, 1983). Willingness to pay is not directly observed, but sale price equals the winning bid for each sale in our choice model. We denote sale price P_q^*, for the winning bid from type k^* and method s^*:

$$P_q^* = \psi_{k^*} + \sigma \ln(M_{qk^*s^*}) + \varepsilon_{qk^*s^*}. \tag{4.4}$$

Substituting and rearranging equations (4.3) and (4.4), the probability density and the cumulative density functions of the random error are defined by

$$\begin{aligned} \varepsilon_{qk^*s^*} &= P_q^* - \psi_{k^*t} - \sigma \ln(M_{qk^*s^*}) \\ \varepsilon_{qks} &< \tilde{P}_q^* - \psi_{kt} - \sigma \ln(M_{qks}) \; \forall \; \{k,s\} \neq \{k^*,s^*\} \end{aligned} \tag{4.5}$$

where $\tilde{P}_q^*$ is introduced to adjust the winning bid price to account for brokerage fees. If a bid is collected via a broker, the seller is required to pay the brokerage fee. To reflect this difference in the seller's realized price as a result of the brokerage fee, we scale the bids that do not win. $\tilde{P}_q^* = (1-\tau) \times P_q^*$ for bids that are collected through non-brokered means when the quota is sold through a broker, $\tilde{P}_q^* = \frac{1}{1-\tau} \times P_q^*$ for bids that are collected through a broker when the quota is sold through non-brokered means, and $\tilde{P}_q^* = P_q^*$, otherwise.

Following (Lerman & Kern, 1983), from the definition of the generalized extreme value distribution, the probability of selling quota to bidder type k^* using sale method s^* is:

$$\begin{aligned} Prob_q(Y_{k^*s^*}) &= f_e(P^* - \psi_{k^*} - \sigma \ln(M_{k^*s^*})) \prod_{ks \notin k^*s^*} F_e(\tilde{P}^* - \psi_k - \sigma \ln(M_{ks})) \\ &= \frac{1}{\sigma} e^{-\frac{1}{\sigma}[P^* - \psi_{k^*} - \sigma \ln(M_{k^*s^*})]} exp\{-e^{-\frac{1}{\sigma}(\tilde{P}^* - \sigma \ln \sum_{k,s} exp\{\frac{1}{\sigma}[\psi_k + \sigma \ln(M_{ks})]\})}\}, \end{aligned} \tag{4.6}$$

which is amenable to estimation via maximum likelihood.

However, a problem remains in that the researchers generally do not observe the number of bids (M) that each seller is able to gather from each bidder type k through both brokered and non-brokered methods of sale. Instead, we observe only the characteristics of the winning bid, including winning bidder type and method of sale by which the winning bid was collected. This issue is conceptually similar to estimating a choice model when the underlying choice set is unobserved. We draw on the literature concerning probabilistic choice sets to formulate our model, specifically we adapt a formulation originally developed by Swait & Ben-Akiva (1987) and modified by Başar & Bhat (2004) to model airport choice when consideration sets vary among travelers.

Given that any number of potential bidders is theoretically feasible for a given quota sale up to the total number of eligible bidders of each type, we define the number of bids collected from each type k as binomially distributed. The probability of a bid for each bidder of type k and method of sale s using a logit transformation to restrict probabilities to (0,1) is:

$$\rho_{qks} = \frac{1}{1 + e^{-\alpha_s - \lambda_s' w_{qk}}}, \tag{4.7}$$

where w_{qk} represents the quota q seller's attributes with respect to bidder category k, and λ_s represents the corresponding coefficients to be estimated, which vary by method of sale s.

Assuming the probability of gathering bids from each type is independent across types, the probability of gathering at least one bid from bidder type k through method of sale s is:

$$Prob(M_{qks} \geq 1) = \frac{1 - (1 - \rho_{qks})^{N_k}}{1 - \Pi_{k,s}(1 - \rho_{qks})^{N_k}}, \tag{4.8}$$

where the denominator normalizes the probability to remove the possibility that the sale has not gathered at least one bid across both methods of sale and all bidder types.

The unconditional probability of selling to bidder type k using sale method s is equal to the probability of observing at least one bid from this type and sale method multiplied by the conditional probability of choosing type k and method s over the alternatives:

$$Prob_q(Y_{ks}) = Prob_q(Y_{ks}|M_{ks} \geq 1) \times Prob_q(M_{ks} \geq 1), \tag{4.9}$$

where Y_{qks} equals 1 if quota sale q is bought by type k through sale method s and zero otherwise.

The definition of $Prob_q(Y_{k^*s^*})$ from equation (4.6) can be modified to reflect $Prob_q(Y_{ks}|M_{ks} \geq 1)$ by replacing M_{ks} with the conditional expected number of bids collected for each bidder type and method of sale. For all combinations of s and k that did not submit the winning bid the expected number of bids is equal to the mean of the unconditional binomial distribution, $E[M_{qks}] = \rho_{qks}N_k$. However, in order for bidder type k to have submitted the winning bid through a particular method of sale s, it is necessary for at least one k-type bidder to have submitted a bid through s. The expected number of bids collected for the winning bidder type k^* through chosen sale method s^* conditional on collecting at least one bid is:

$$E[M_{qk^*s^*}] = E[M_{qks}|M_{qks} \geq 1] = \frac{\rho_{qks}N_k}{1-(1-\rho_{qks})^{N_k}}. \tag{4.10}$$

The log likelihood of the full unconditional probability defined in equation (4.9) of observing a quota sale to bidder type k using sale method s is defined as:

$$\begin{aligned} \mathbb{L} = N\ln\sigma - \frac{1}{\sigma}\sum_q [P_q^* - \psi_{k^*} - \sigma\ln(E[M_{qk^*s^*}])] - \sum_q\sum_{k,s} e^{\frac{1}{\sigma}(\psi_k + \sigma\ln(E[M_{qks}]) - \tilde{P}_q^*)} \\ + \sum_q \{\ln[1-(1-\rho_{qk^*s^*})^{N_k^*}] - \ln[1-\prod_{ks}(1-\rho_{qks})^{N_k}]\}. \end{aligned} \tag{4.11}$$

4.3 Application

We begin by estimating the mean willingness-to-pay for Alaskan halibut individual fishing quota shares among bidders from different community sizes and locations. The Alaskan halibut fishery transitioned to an individual fishing quota (IFQ) system in 1995, replacing a policy of limited entry with seasonal closures, which resulted in a race to fish. At the program's inception, quota shares were granted to any individual who owned or leased a vessel that landed catch in the commercial fishery in 1988, 1989, or 1990 based on the best five fishing seasons during the time period 1984-1990. These quota shares granted the recipients a right to catch a proportion of the halibut catch each season effectively in perpetuity, which could then be transfered to other eligible quotaholders.

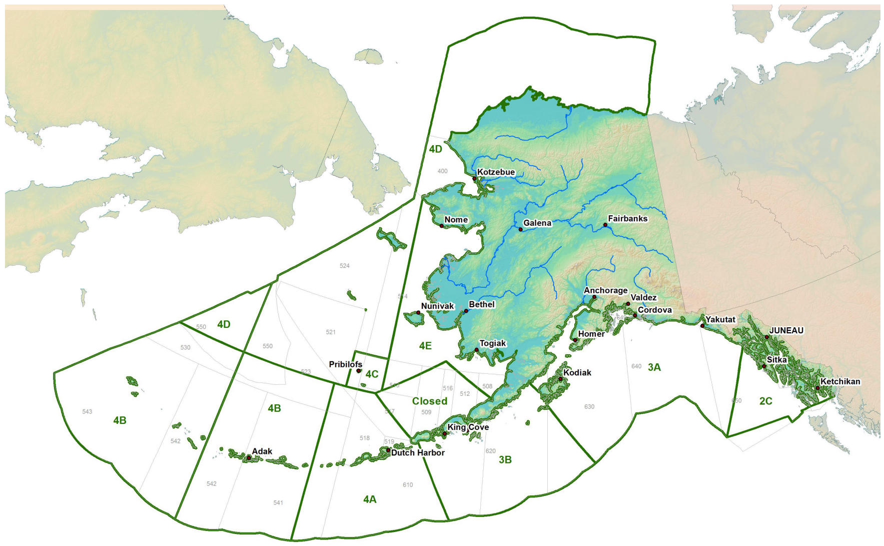


Figure 4.1: **Halibut Quota Management Areas** reprinted from (NOAA, 2019a)

Total mortality limits for each fishery area are set prior to each fishing season by the International Pacific Halibut Commission (IPHC), a bilateral regional fishery management organization responsible for halibut management along the Pacific coast of mainland United States, British Columbia, and Alaska. Within the IPHC's mortality limits, Alaskan commercial seasonal catch limits are determined by the North Pacific Fishery Management Council for each of the eight management areas (figure 4.1). At the beginning of each season, quota shares are translated into quota pounds that can be caught during each fishing season based on the total allowable catch for that season for each IFQ area. Quota shares that are assigned to one area can only be used to catch halibut in that area. Quota are also assigned to specific vessel classes, primarily based on vessel size, restricting the halibut that can be caught using the quota to the class of vessel corresponding to the quota. Additional information on the Alaskan halibut IFQ policy is available in the previous chapter, and information has appeared elsewhere in government reports (NOAA Fisheries, 2015; NMFS, 2016) and the academic literature (Kroetz et al., 2015; Szymkowiak & Himes-Cornell, 2015).

We divide all eligible bidders into five distinct categories based on location and community size. Travel distance is a ubiquitous component in fishing location choice models (e.g., Haynie & Layton, 2010; Mistiaen & Strand, 2000; M. D. Smith, 2005), and population adjacent to the IFQ area is thought to influence quota demand (Szymkowiak & Himes-Cornell, 2015). For that reason, we divide up bidders according to three factors, whether their community is adjacent to an IFQ area, whether it is elsewhere in Alaska, and whether it is outside of Alaska.

Within bidders from communities adjacent to the IFQ area, we further distinguish between bidders from small, medium, and large communities. Previous work has noted that Alaskan commercial halibut quota has migrated from small rural fishery-dependent communities (Carothers et al., 2010). A possible rationale for quota migration is that small Alaskan communities tend to have fewer financial resources to draw upon compared to larger communities, particularly larger communities outside of Alaska (Szymkowiak & Himes-Cornell, 2015). Applying the random bidding model to these categories will allow us to estimate the magnitude of differences in average quota value between these communities directly.

4.3.1 Alaska halibut IFQ policy change

While transfer of quota shares (the permanent right to fish) is common in the fishery, transfers of quota pounds (the right to catch fish in a season) is generally only permitted when also transfering the quota shares they derive from. An exception to this restriction is the Guided Angler Fish (GAF) program implemented as part of the catch share plan in 2014. Many of the details of this program are described in NOAA (2019b) and Lew et al. (2016). The GAF program allows commercial quota shareholders in IFQ areas 2C and 3A to transfer small amounts of quota pounds to charter halibut permit holders. Allowable GAF transfers per-person are limited to 1500 pounds of quota or up to 10% of the commercial quota shareholder's total quota pounds in area 2C, whichever is greater. Area 3A limits are similar except up to 15% of eac h commercial quota shareholder's quota in area 3A may be transfered to the guided charter sector. Rather than allocating quota strictly between the commercial and recreational fishing sectors, the GAF policy allows some flexibility in allocation. In an idealized economic model this flexibility would promote greater economic efficiency (Arnason, 2009), though this ideal is often not achieved in practice (Abbott, 2014).

Halibut recreational fishery limits are placed in terms of a bag limit rather than pounds. The conversion of quota pounds to fish is based on a conversion factor set annually by the National Marine Fisheries Service. In 2014, 26.4 quota pounds were required for area 2C and 12.8 pounds for area 3A per additional charter sector fish. This conversion was increased in 2015 to 67.3 pounds and 38.4 pounds for areas 2C and 3A, respectively. Once a charter permit holder has purchased sufficient quota pounds, the GAF can then be used in the charter fishery to catch up to the limits of the unguided sport fishery which have less restrictive daily and seasonal bag limits. Any unused GAF are transfered back to the original permitholder at the end of the fishing year.

In addition to modeling the willingness-to-pay of different bidder categories across all years of quota policy, we also estimate the impact of GAF on willlingness-to-pay for quota among eligible buyers from small- and medium-sized communities adjacent to the IFQ area. One of the arguments advanced in favor of GAF and other flexible allocation schemes for Alaskan halibut is that it would partially reverse quota migration. Soliman (2014) notes that charter halibut fishing does not require intensive transportation infrastructure or a large industrial base to maintain the activity. Instead, charter fishing can easily take place in relatively remote areas, and charter fishers can attract tourists which can benefit the local economy more broadly. However, GAF would also provide an alternative possible source of income for commercial quota shareholders, who would be able to sell their annual quota to charter fishers rather than fish the quota themselves if they find that to be economically preferable. This diversification in possible income sources may increase quota share prices, which, due to the relative lack of financial resources among commercial fishers in smaller communities, may adversely impact fishers from small or medium-sized communities relative to large communities. Charter fishing quota may also crowd out commercial quota in these areas if there is some capacity constraint on total fishing activity.

4.3.2 Model Specification

We define the observed deterministic component ψ_{qkt} as comprising three additively separable components. First, a time-varying component common to all categories that captures changes to the latent average underlying willingness-to-pay over time (denoted g_t). Second, a common fixed effect for characteristics of the quota sale, denoted by the vector R, and including an indication of whether the quota is part of a block, and quota pounds that were included in the quota transfer. Third, a unique fixed effect (β) for each combination of buyer category (k) and vessel class. As in the previous chapter, we estimate the model using a log-transformation in order to restrict predicted prices to positive values:

$$\ln(\psi_{qkt}) = g_t + R_q'\gamma_r + I_{k\times vessel}'\beta_{k\times vessel}. \tag{4.12}$$

We draw from the results in the previous chapter to estimate the bid-collection rate for non-brokered sale method to estimate ρ in equation 4.7. Non-brokered bid collection rate for each category k is estimated to be a function of the number of bidders of type k that live in the same city as the seller, that deliver catch to the same ports, and that sell catch to the same processor. Given the results of the previous chapter, we assume that brokers draw bids equally from each bidder type in proportion to the number of bidders of that type among eligible quota shareholders. This leaves α_{broker} to be estimated, but as we do not observe the number of bids or the underlying willingness-to-pay of bidder types, the model is under-identified and this parameter cannot be estimated based on the data. As our focus is on the relative bid-collection rate between the two methods as well as the estimates of underling willingness-to-pay by bidder type, we identify the model by setting α_{broker} equal to 3%. This allows the other parameters to be estimated and does not appreciably affect the estimates. We re-estimate the model for a variety of α_{broker} values ranging from 0.1% to 50% and find the choice of appreciably impacts only the magnitude of the $\alpha_{nonbroker}$ and λ_s coefficients in the bid-collection sub-model and the intercept term for the common time-varying component in equation 4.12.

$$\begin{aligned}
\rho_{iks} &= \frac{1}{1+e^{-\alpha_s-\lambda_s' w_{ik}}}, \text{ for } s = nonbroker \\
\rho_{iks} &= 3\%, \text{ for } s = broker
\end{aligned} \tag{4.13}$$

4.3.3 Data

As in the previous chapter, we make use of comprehensive confidential transfer data for years 2000-2017 available through AKFIN. We again limit the transfer report price data to trades that are arms-length for which consistent price data can be calculated. We focus in particular on areas 2C and 3A, which are the areas in which the GAF policy was implemented. They are also the areas that have by far the most quota market activity. Class A quota is also omitted from the estimation results. This class refers to quota that can be used on catcher-processor vessels, and is governed somewhat differently to the other three vessel classes. Of principal importance, the sale of quota pounds is not restricted for class A vessels, and quota share transfers are sparse as a result. After data processing, there are 1355 arms-length transfers with valid prices in area 2C and 2054 in area 3A, respectively. After trimming the extreme outliers with standard deviations greater than 4, we are left with 1345 observations in area 2C and 2047 in area 3A. Together, areas 2C and 3A comprise over 70% of the total sales in the halibut IFQ market.

To identify bidder communities, we rely on address information provided by AKFIN. Particularly, we use the city and state of the bidder to geocode the results to assign a geocode to each unique Alaskan city in the dataset. This geocode is used to define whether the bidder's community is located adjacent to the IFQ area in question. We define any community south of longitude 137 as adjacent to 2C, and any community between longitude 137 and 156 and east of latitude 62 as adjacent to area 3A. The AKFIN data also includes a database of each individual that is eligible to receive quota and the date at which they became eligible, if appropriate. However, address information is only present for individuals who have owned quota. As a result, we only use quota holdings database to define the set of eligible bidders.

We use the name of the city to match to census information for year 2010 to obtain the population for each Alaskan city.[3] Using Carothers et al. (2010) for guidance, we define large communities as any with a population above 7500. Medium communities have a population of 1501 to 7500, while small communities are defined as any community with a population of 1500 people or fewer.[4] Communities for each area and size appear in table 4.1.

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[3]We considered using 2000 Census data and imputing the population for the intervening years. However, only one community changed categories in the intervening time between the 2000 and 2010 census, so we judged the added value of this approach to be insufficient to justify the imputation procedure here.

[4]Carothers et al. (2010) similarly breaks communities into small, medium, and large categories, and similarly classifies any community under 1500 people as 'small'. However, a 'medium' community size in their paper is any that has between 1500 and 2500 people, while large communities have a population between 2500 and 7500. As they focus on small rural fishing communities, any community with a population above 7500 are not categorized. We combine their medium and large communities into a single 'medium' community category because their results suggest largely similar transfer patterns for these two groups, and add a 'large' category in order to distinguish those communities with populations above 7500.

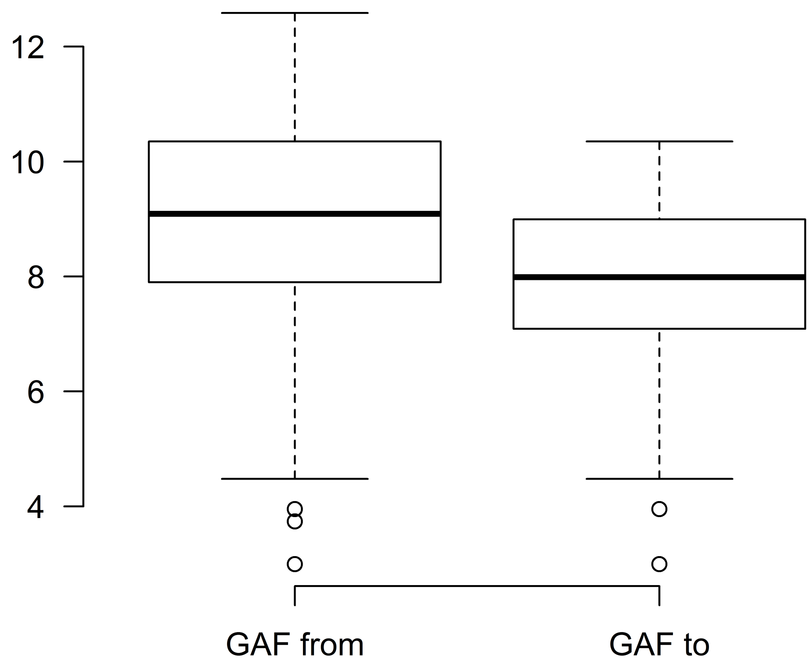
Table 4.1: List of Alaskan communities by size category, adjacent to areas 2C and 3A.

	Area 2C	Area 3A
Large	Ketchikan, Juneau, Sitka	Anchorage, Wasilla
Medium	Haines, Petersburg, Wrangell	Anchor Point, Big Lake, Cordova, Fritz Creek, Homer, Kenai, Kodiak, Nikiski, Palmer, Seward, Soldotna, Sterling, Valdez, Willow
Small	Angoon, Coffman Cove, Craig, Edna Bay, Elfin Cove, Gustavus, Hoonah, Hydaburg, Hyder, Kake, Klawock, Metlakatla, Naukati Bay, Pelican, Point Baker, Port Alexander, Skagway, Tenakee Spring, Thorne Bay, Whale Pass	Chenaga, Chiniak, Chitina, Clam Gulch, Cooper Landing, Cooper Center, Halibut Cove, Kasilof, Larsen Bay, Moose Pass, Nikolaevsk, Ninilchik, Nondalton, Old Harbor, Ouzinkie, Port Graham, Port Lions, Seldovia, Sutton-Alpine, Whittier, Yakutat

Data on a seller's home city is also incorporated in the bid-gathering sub-model defined in equation 4.13. Additional data to estimate this equation comes from AKFIN landings data, and includes port identification information for each landing as well as the unique identification number for the registered processor that purchased the fish. As in the previous chapter, we use the year prior to the transfer in order to define this relationship as many transfers take place before the seller lands any fish for the relevant year. Also as in the previous chapter, count data is transformed using the inverse hyperbolic sine method due to high skewness and large outliers in the data, as well as a large number of zeroes. In addition, we consider the possibility that bid-collection rates do not scale with the number of potential social network relationships and estimate an additional set of models that use binary variables to indicate whether the seller resides in a city that is associated of the respective bidder type, or shares a port or processor with a fisher of that bidder type.

The transfers database also includes GAF transfers, including the reported community in which the GAF recipient resides. While our primary analysis concerns the price of quota shares in the

Figure 4.2: Logged origin and destination community populations for quota transfers under the GAF program.



commercial sector, we also use GAF transfer data to evaluate whether the GAF program indeed reverses the quota migration process by transfering GAF from larger communities and toward smaller ones. Figure 4.2 below compares the population of GAF source communities as well as recipient communities, and shows that GAF recipients do indeed reside in smaller communities than the GAF sources. A t-test shows GAF source communities are statistically significantly larger than the GAF recipient communities, confirming the hypothesis that allowing transfers to the charter halibut sector would encourage quota transfers toward less populated communities (Soliman, 2014).

4.4 Results

Model estimates for area 2C appears in table 4.2 and estimates for area 3A appears in 4.3. In order to avoid confusion over interpretation of point estimates bidder categories are not included in the tables, but the implied distribution of willingness-to-pay among bidder categories across the four models based on the point estimates in each model are summarized in figures 4.3 and 4.4.

Turning our attention first to the bid-gathering sub-model, the relative magnitude of the α parameters indicate that the non-brokered method of sale collects bids at only about one-seventh the rate of brokered bid collection except among bidders that reside in the same city as the seller. The results suggest that non-brokered bid-collection is primarily focused on bidders that reside in the same city as the seller. The coefficients on both shared port and shared processor are negative. By contrast, the shared city coefficient is positive and highly statistically significant across all model specifications. The magnitude of the shared city coefficient suggests that sellers are able to gather non-brokered bids at more than twice the rate among bidder types that they share a city with compared to other bidder types.[5]

The model results in an implied distribution of willingness to pay among quota bidders, with different means for each bidder category. These implied distribution for bidders from small, medium, and large communities for area 2C and area 3A are reported in figures 4.3 and 4.4, respectively. Across models (2)-(4), which use trimmed data to estimate the parameters, the results are nearly identical. Model (1), for which the data are not trimmed differs somewhat across both areas. The scale parameter is significantly greater than for models (2)-(4) implying a much wider distribution of willingness-to-pay for quota. This results in a lower estimated mean for each bidder category

[5]The binary version of the three bid-collection variables had very high multi-collinearity (greater than 0.7 across all three measures and both areas), so a model where all three variables assume a binary form is not estimated.

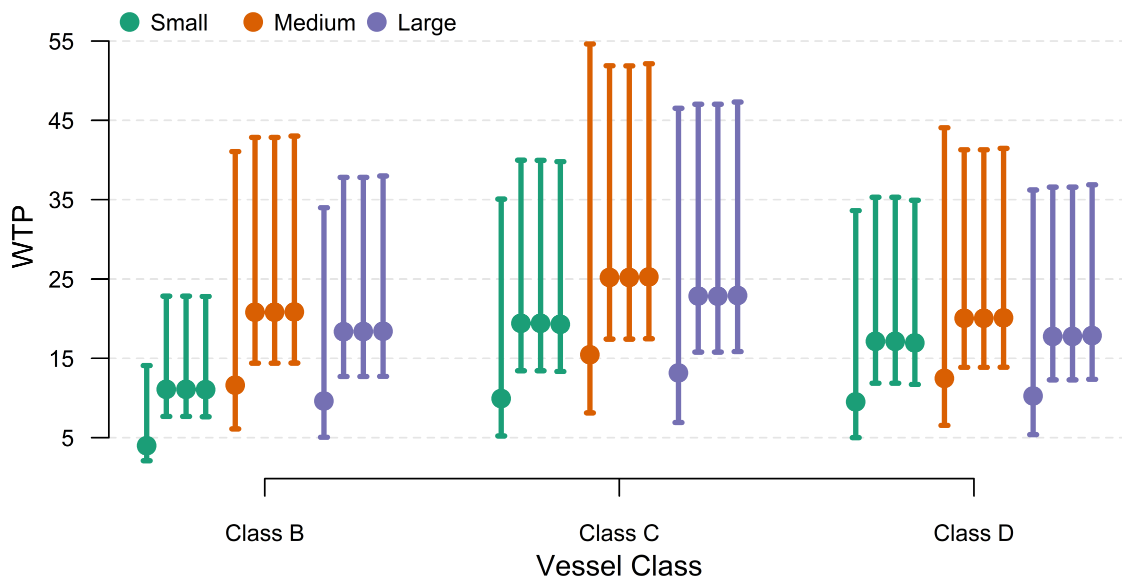
Table 4.2: Area 2C models of willingness-to-pay for halibut quota shares in terms of logged price per pound. Brokered bidding probability fixed at 3%. Standard errors in parenthesis. All models also include a b-spline with annual knots to control for change in the fishery over time as well as a fully-interacted set of bidder category and vessel classes.

	Dependent Variable: Halibut quota share price (logged)			
	(1)	(2)	(3)	(4)
$1/\sigma$	2.626	4.630	4.632	4.623
	(0.053)	(0.087)	(0.087)	(0.087)
Brokered bidding				
Constant	-3.476	-3.476	-3.476	-3.476
	(fixed)	(fixed)	(fixed)	(fixed)
Non-brokered bidding				
Constant	-5.526	-5.794	-5.810	-5.872
	(0.109)	(0.111)	(0.095)	(0.100)
ihs(Shared City)	0.271	0.269	0.266	
	(0.022)	(0.022)	(0.020)	
Share city binary				1.641
				(0.123)
ihs(Shared Port)	0.074	0.004		
	(0.111)	(0.120)		
ihs(Shared Processor)	-0.125	-0.015		
	(0.110)	(0.120)		
Quota qualities				
Blocked	−0.114	−0.015	-0.015	-0.016
	(0.033)	(0.020)	(0.020)	(0.020)
Quota Pounds (thousands)	0.020	0.023	0.023	0.023
	(0.004)	(0.002)	(0.002)	(0.002)
Obs.	1355	1345	1345	1345
Log Likelihood	-3146	-2365	-2365	-2363
AIC	6377	4815	4811	4807

Table 4.3: Area 3A models of willingness-to-pay for halibut quota shares. Brokered bidding probability fixed at 3%. Standard errors in parenthesis. All models also include a b-spline with annual knots to control for change in the fishery over time as well as a fully-interacted set of bidder category and vessel classes.

	Dependent Variable: Halibut quota share price (logged)			
	(1)	(2)	(3)	(4)
$1/\sigma$	1.233	3.846	3.861	3.847
	(0.017)	(0.056)	(0.056)	(0.056)
Brokered bidding				
Constant	-3.476	-3.476	-3.476	-3.476
	(fixed)	(fixed)	(fixed)	(fixed)
Non-brokered bidding				
Constant	-4.947	-5.396	-5.489	-5.499
	(0.081)	(0.080)	(0.070)	(0.072)
ihs(Shared City)	0.169	0.202	0.190	
	(0.018)	(0.018)	(0.017)	
Share city binary				0.982
				(0.098)
ihs(Shared Port)	-0.141	-0.069		
	(0.074)	(0.074)		
ihs(Shared Processor)	0.034	0.022		
	(0.081)	(0.080)		
Quota qualities				
Blocked	-0.332	-0.174	-0.172	-0.171
	(0.054)	(0.018)	(0.020)	(0.018)
Quota Pounds (thousands)	0.012	0.006	0.006	0.006
	(0.002)	(0.001)	(0.001)	(0.002)
Obs.	2054	2047	2047	2047
Log Likelihood	-6146	-4033	-4036	-4043
AIC	12375	8151	8152	8166

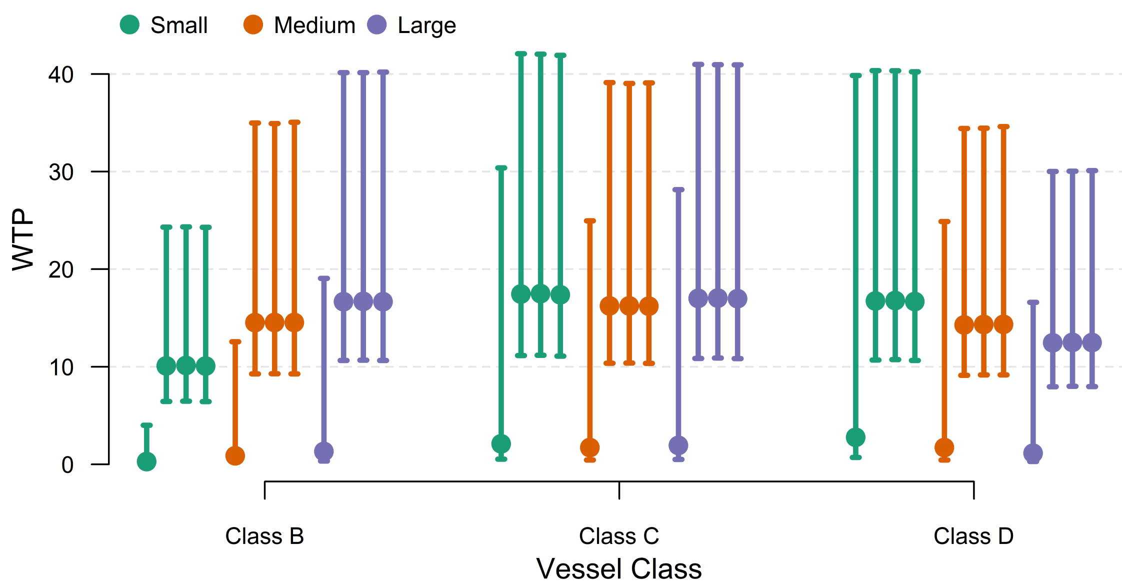
Figure 4.3: Point estimate of distribution of willingness-to-pay for bidders from small, medium, and large communities based on models (1)-(4) reported in Table 4.2. The median is represented by the point and the middle 95% of the distribution represented by the line. Willingness-to-pay is based on unblocked quota and no quota pounds sold on January 1, 2016.



for model (1) compared to models (2)-(4), but a wider middle 95% so that in many cases the upper range of the distributions nearly match. Because our model assumes we only observe the highest bid, it would make sense that the upper ranges of the implied distributions of willingness to pay are more robust to different model specifications than are the medians. Even so, the relative pattern of willingness-to-pay across the buyer categories is the same for model (1) as it is for models (2)-(4). This suggests the relative patterns of buyer willlingness-to-pay are robust to outliers even if the means or medians of estimated willingness-to-pay are not.

Going forward, we use model specification (3) for estimates in both areas, which excludes shared ports and processor data in the bid-collection sub-model. According to AIC, there is little difference between the model formulations that use the IHS transformation and binary representation

Figure 4.4: Point estimate of distribution of willingness-to-pay for bidders from small, medium, and large communities based on models (1)-(4) reported in Table 4.3. The median is represented by the point and the middle 95% of the distribution represented by the line. Willingness-to-pay is based on unblocked quota and no quota pounds sold on January 1, 2016.



of the ‘shared city’ variable, possibly suggesting that there is a limit to the extent to which non-brokered bid-gathering rates can scale, even if the bidder lives in the same city. For consistency, we use the formulation with the IHS transformation of the shared city variable, but results are substantively similar when using model (4) instead.

The estimated mean willingness-to-pay across for each of the five bidder types and three vessel categories based on model (3) is presented in figure 4.5 and 4.6. Across both areas, bidders in small communities display a markedly lower willingness-to-pay for class B quota than other bidder types within the area. This likely reflects the lack of infrastructure in these areas required to support larger vessels, and could be exacerbated by the lack of financial infrastructure that prevents bidders for more expensive class B quota. As vessel size classes decline, bidders from small communities are willing to pay more for quota relative to their counterparts in larger communities. In area 3A, we estimate bidders from small communities are willing to pay more for vessel D quota than any other bidder type. However, in area 2C small community bidders still have lower willingness-to-pay than medium and large communities. In area 2C, medium-sized communities consistently are willing to pay the most on average for quota across all vessel classes. By contrast, large communities are willing to pay more for vessel class B and C quota in area 3A.

These divergent results could partially be explained by geographic isolation of small communities in area 2C. Most area 2C communities are relatively isolated from medium and large-sized communities. Moreover, previous research has reported relatively intense competition for quota in area 2C, driven by non-Alaskan fishers from Seattle and by the large population adjacent to area 2C (Szymkowiak & Himes-Cornell, 2015). This could put additional strain on resources for bidders from small communities that do not have as much ready access to capital as bidders elsewhere. In area 3A, by contrast, many of the small communities are located near Kodiak and other major fishing hubs, which may allow for greater logistical and financial support for their fishing activity.

Figure 4.5: Estimated mean willingness-to-pay for area 2C quota across five bidder types; bidders adjacent to the IFQ area residing in small, medium, and large communities, bidders from Alaska but not adjacent to the area (Other-AK), and bidders from outside of Alaska (non-AK).The WTP estimate is applied here to unblocked quota sale with no quota pounds as of January 1, 2016 and assuming a brokered bid collection rate of 3%.

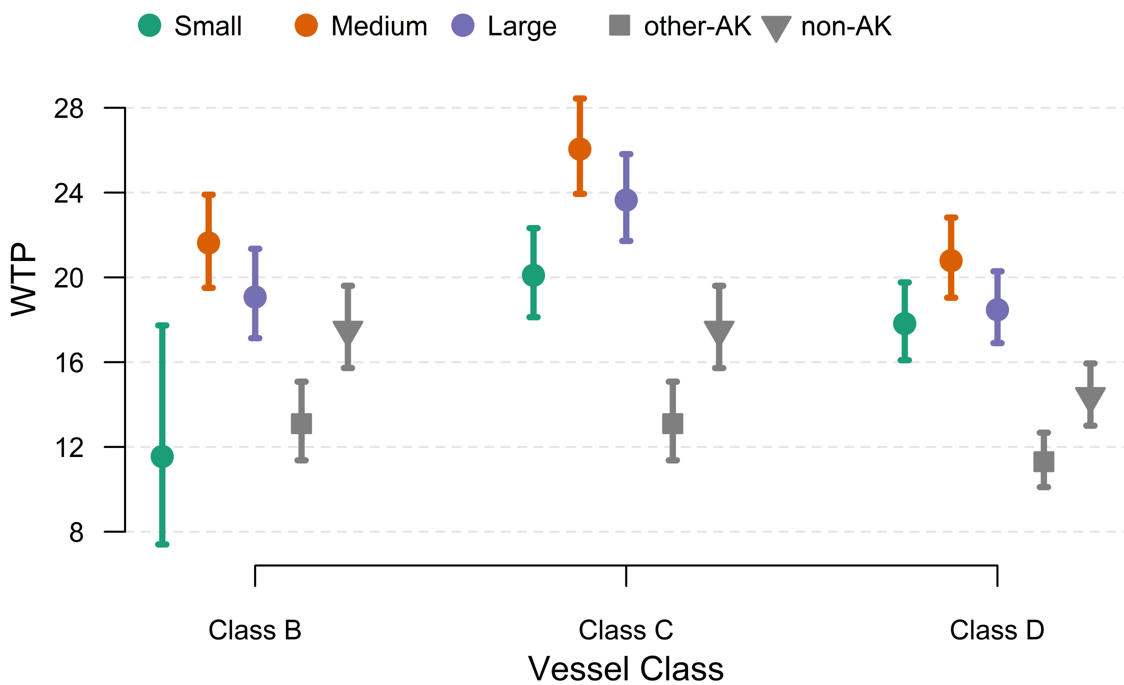
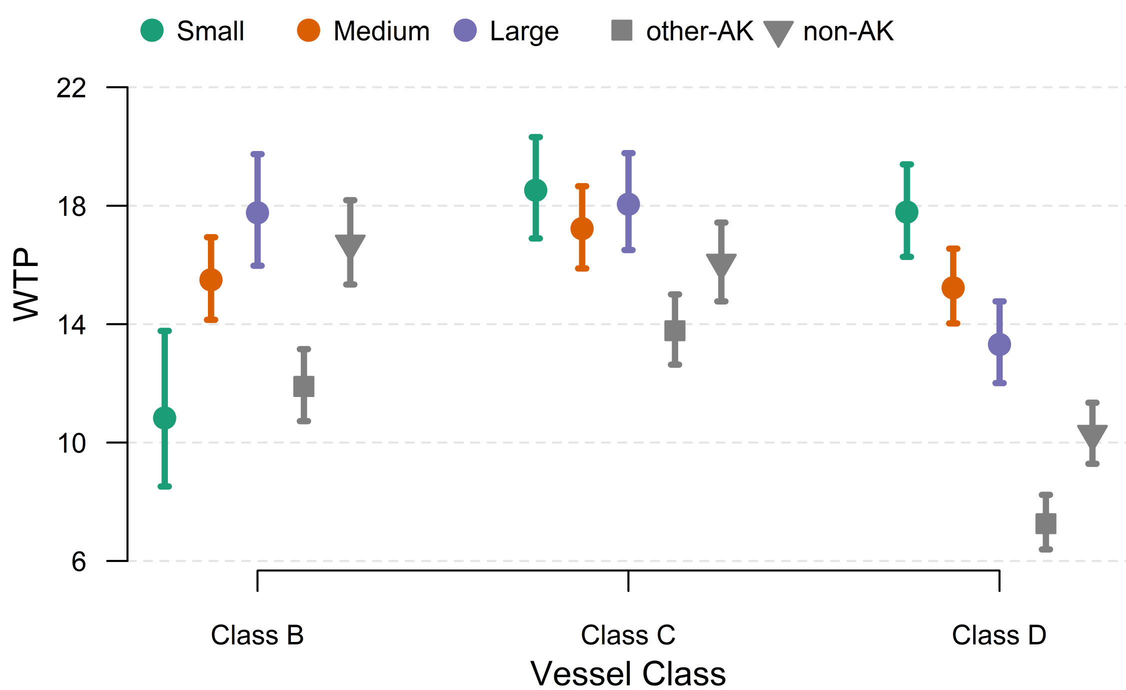


Figure 4.6: Estimated mean willingness-to-pay for area 3A quota across five bidder types; bidders adjacent to the IFQ area residing in small, medium, and large communities, bidders from Alaska but not adjacent to the area (Other-AK), and bidders from outside of Alaska (non-AK).The WTP estimate is applied here to unblocked quota sale with no quota pounds as of January 1, 2016 and assuming a brokered bid collection rate of 3%.



4.4.1 GAF model and results

To test for the effect of the GAF transfer program on willingness to pay, we use a regression discontinuity design.[6] Regression discontinuity is a quasi-experimental method in which causal inferences are drawn based on a discontinuous change in policy at some defined threshold. We use January 13, 2014 as the data of policy implemenation of the GAF through the 2014 catch share plan as the threshold.

As vessel class B is traded relatively infrequently and is rarely used in GAF transfers, we exclude class B data from our estimates. Our estimation procedure remains largely the same as described above. We again estimate a willingness-to-pay based on equation 4.1. However, we define an alternative specification for ψ_{qkt} as a local linear model:

$$\psi_{qkt} = R_q'\gamma_r + \theta_1 I_{t>0} + \theta_2 t + \theta_3 t I_{t>0} + I_{k\times vessel}'\beta_{0,k\times vessel} + I_{t>0} I_{k\times vessel}'\beta_{1,k\times vessel} \tag{4.14}$$

where transaction date t is normalized such that $t = 0$ at the GAF date threshold. The first term controlling for intrinsic quality of the quota sale remains unchanged. The discontinuity itself is equal to θ_1. Rather than controlling for changes over time using b-splines, we use a flexible linear specification, where t has a linear trend θ_2 prior to the discontinuity and a linear trend of $\theta_2 + \theta_3$ after the discontinuity. Any change in willingness-to-pay after the GAF policy for a bidder category-vessel class is captured by $\beta_{1,k\times vessel}$.

Following recent recommendations in Athey & Imbens (2017) and Gelman & Imbens (2019), we use a local linear approach rather than a global polynomial to control for changes over time. We

[6] Given the other IFQ areas it could also be possible to conduct a difference-in-differences design. However, the GAF was implemented in the two most active quota shared markets with higher quota share prices than other areas, making it unlikely we could identify a proper counterfactual using an IFQ area outside 2C and 3A.

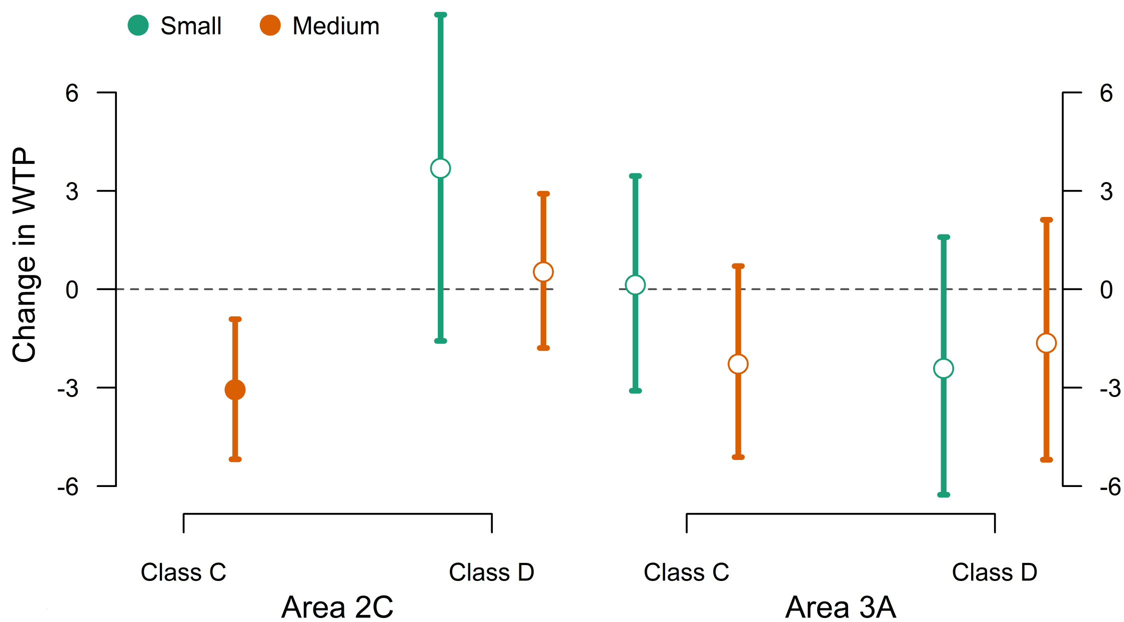
specify an Imbens-Kalyanaraman (Imbens & Kalyanaraman, 2012) bandwidth equal to 2.07 years for area 2C models, and 2.64 years for area 3A models. This means that only observations that fall within 2.07 years and 2.64 years of the GAF policy implementation on January 13, 2014 will be included in area 2C and area 3A estimates, respectively. Finally, we weight the model using a triangular kernel, disproportionately weighting sales that occur near the discontinuity.[7] Both the bandwidth and weighting calculations are conducted using the rdd package in R (Dimmery, 2016).

We do not have sufficient observations to estimate a fully flexible model that allows a separate discontinuity and kink in the linear trend at the discontinuity threshold for each bidder category. As a result we only report the relative changes to willingness-to-pay for groups as compared to a reference category. In particular, we compare the change in willingness-to-pay among bidders from small- and medium-sized communities relative to the change in willingness-to-pay among bidders residing in large Alaskan communities. In general bidders from large Alaskan communities have easier access to lending institutions and are less constrained by port facilities, so we would expect any discontinuity in this group as a result of GAF policy to be muted compared to the impact on bidders from smaller communities, though large community bidders should still absorb other changes to the fishery such as expectations of future total allowable catch or ex-vessel price changes. This is akin to a difference-in-differences experimental design where large-community bidders are serving as a quasi control group and bidders from small- and medium-sized communities are serving as the 'treatment' groups. Because bidders from large communities serve as our reference category, the relative change in willingness-to-pay among bidders from other communities as a result of GAF policy equals $\beta_{1,k\times vessel}$.

These results are reported figure 4.7. They suggest that willingness to pay among bidders from small communities did not decline more than willingness-to-pay among bidders from large com-

[7] We also test an Epanechnikov kernel, but find the results are almost identical.

Figure 4.7: Estimated change in willingness-to-pay (in dollars per pound of quota shares) for commercial fishery quota due to Guided Angler Fish transfers relative to bidders in large communities.



munities as a result of the GAF policy. If anything, small community bidders appear willing to pay over three dollars per quota share pound more for quota after the policy compared to large community bidders, though this estimate has wide error bars. However, there are no observed purchases of vessel C quota by small-community bidders within our bandwidth after the GAF policy is implemented. As a result, we are unable to estimate the change in willingness-to-pay for small-community bidders for vessel class C quota.

Willingness-to-pay for quota among bidders from medium-sized communities in area 2C declined by three dollars per pound of quota shares on average compared to large community bidders as a result of GAF policy. Both estimates for medium-sized communities in area 3A were negative as well, though these estimates were not statistically significant.

4.5 Discussion and conclusion

We have proposed a model based on the random bidding model (Ellickson, 1981; Lerman & Kern, 1983) that can be used to estimate *ex-post* willingness-to-pay for fishing quota among various fishing groups as well as evaluate changes in in willingness-to-pay in response to policy changes. As in previous linear models of prices, the model proposed here takes advantage of observed sales in order to estimate systematic price differences for the buyer type involved in the trade (Harding et al., 2003; Jin et al., 2019; Lee, 2012; Ropicki & Larkin, 2014). An advantage of this model over other formulations, is it does not assume pure bilateral bargaining among a fixed seller-buyer pair. By assuming that sellers collect multiple bids, we can draw inferences concerning buyer demand among bidder categories that were not directly involved in the bilateral trade. Similar adaptations of the random bidding model have been used to estimate real estate demand (Ellickson, 1981; Martínez & Henríquez, 2007; Muto, 2006), and we demonstrate how this method might be applicable to environmental markets as well. While our focus here is on markets for fishing quota share, it may be applicable to other rights-based fishing management schemes as well as other transferable permit systems such as SO_2 or NO_x trading permits.

In particular, we think this method would be valuable in evaluating the distributional impacts of policies. In this example, we apply the model to estimate the relative willingness-to-pay among fishers based on community size. Quota migration and consolidation has been a near-universal feature of quota share policies, and quota consolidation has been observed to take place at the community level as well as the individual level (Carothers et al., 2010). Quota migration may be a part of why smaller communities view quota policies less favorably than other fishers despite the known economic benefits associated with quota share policies (Carothers, 2013). Our results are able to nuance these prior findings and situate them in an economic context. In particular, we find that willingness-to-pay for quota is lower among small community buyers in area 2C compared to bidders in medium and large communities. However, bidders in small communities have a comparable or higher willingness-to-pay for quota fishable on boats under 60 feet compared to bidders in medium and large communities. This could be attributable to the different economic contexts for small communities in two areas. Small communities in 2C tend to be relatively isolated from major fishing hubs leading to higher costs associated with fishing. They also face higher baseline prices associated with purchasing quota, making access to lending institution particularly valuable for potential buyers though these services are less accessible for small communities in area 2C (Szymkowiak & Himes-Cornell, 2015).

In addition, we use the random bidding model within a regression discontinuity design and find little evidence that guided angler fishing permit transfers led to lower willingness-to-pay among eligible quotaholders from small communities. Given the economic argument that allowing transfers between commercial and recreational sections may produce greater economic efficiency (Arnason, 2009) and the recent policy trial with a quota system in the for-hire sector for Gulf of Mexico red snapper and gag grouper (Abbott & Willard, 2017) the question of how flexible allocation might affect willingness-to-pay among different segments of commercial harvesters may be applicable to many contexts. We did not find any evidence that allowing quota transfers to the for-hire sector particularly disadvantaged harvesters from small communities. However, we did find a decrease in willingness-to-pay for class C quota among bidders from medium-sized communities in area 2C. There were similar results for medium-sized communities in area 3A, though these had wider errors and were not statistically significant. It is unclear from our results why medium-sized communities would be affected by the policy but not small communities, and why this effect would be limited to class C quota. One possible explanation is that medium-sized communities tend to disproportionately hold class C quota, and are also recipients of the GAF transfers. By allowing more charter fishing, the GAF policy may have decreased the demand for quota among fishers in these communities instead increased their charter fishing activity, thereby decreasing their willingness-to-pay for commercial quota compared to large communities where charter fishing is less common.

In this paper, we applied our proposed model to distributional questions of policy change to the quota market itself. However, in many cases it could be applied to changes in the fishery as a whole. The willingness-to-pay for quota shares reflects the *in situ* value of the fish, so any changes in willingness-to-pay may be interpreted as change to the value of the fishery as an economic resource. It is possible to evaluate a wide range of policy and biological changes using this model, including international seafood trade policy, green labels or other fishery certification measures, changes in the scope of management such as ecosystem-based management, as well as the effects of climate change.

In addition to estimating the distribution of willingness-to-pay for quota, our proposed model may also be used to evaluate methods of sale. In particular, the emergence of brokers in many fisheries is often taken as a sign of a well-functioning quota market. However, participation in brokerage may be low due to high fees charged by brokers or by low levels of bid-collection. Our model may be used to estimate relative bid-collection rates for alternative methods of sale. it ay also be used to evaluate an individuals latent implicit bid-collection ability. In the absence of a market-maker such as a broker, sellers would have to gather bids using their own capacity. Network characteristics of fishing quota trading (van Putten et al., 2011) and price premiums associated with advantageous network positions (Ropicki & Larkin, 2014) may reflect differential bid-gathering ability of sellers.

We used population-based categories to define halibut fisher types, but additional categories of interest could include reliance on fishing, such as measured by (Himes-Cornell & Kasperski, 2016). There is a strong overlap between community size and fishing reliance; as community size falls, reliance on fishing activity tends to increase. In that respect, our results may be partially attributable to differences in reliance on fishing. Degree to which fishing activity is diversified (Cline et al., 2017) and remoteness of the quotaholder's community (Carothers et al., 2010) may also be important modeling considerations that can be incorporated into later work. Future work may also examine differences in scale parameters among different buyer groups as well as differences in location parameters. It is possible that certain types of buyers have greater variance in their underlying willingness to pay than others.

There are several shortcomings of our approach that may be resolved by additional data in future work. In particular, we do not consider heterogeneity among sellers. For instance, we assume the amount of time to sale is equal across all sellers. As bid-collection time increases, sale price would also be expected to increase. Some sellers may be able to spend more time collecting bids than others. Currently data on time on the market or rejected bids are not collected for quota sales, but this could help to refine our results and may explain some of the variance in the quota price. While we draw inferences on willingness-to-pay based on buyer behavior, the model does not incorporate seller behavior or draw inferences about a seller's willingness-to-pay based on the quota price. A more elaborate adaptation of this model to incorporate both the seller and buyer side of the market would be a valuable addition to this research. Finally, we assume that bidders bid their willingness-to-pay. However, bids may be strategically determined as a function of the volume of quota shares currently on the market. While limited data is available on quota for sale and ask prices via broker websites, this data is not systematically collected to model quota share prices. The bilateral bargaining solution would still be a function of bidder willingness-to-pay, but this additional information may be used to estimate when bidders offer less than their willingness-to-pay due to the volume of other alternative purchases that might be available.

Appendix A

APPENDIX TO CHAPTER 1

A.1 Alternative model specification

In the main text we use state- and monthly fixed effects to control for differences in TIC over space and time. An alternative to the additive model specification reported in the main body of the text is to control for state-specific time-varying factors. We do this by using a separate b-spline for each state. B-splines are a semi-parametric method for controlling for . The downside to this approach is that it involves much greater dimensionality in the model, possibly resulting in overfitting.

Model (1) in the table below displays the results using each of the quality factor scores. There are a handful of extreme factor scores, particularly for the connectivity factor. Model (2) truncates both quality factors to the range [-3,3] in order to reduce the possible effects of non-linearity between factor scores and TIC at the extreme tails of the quality distribution. In particular, there may be decreasing returns to quality, and truncation is one method to control for this possible diminishing relationship between TIC and advisor quality factor scores.

Table A.1: **Alternative Regression of True Interest Cost on Bond and Advisor Characteristics.** State-specific cubic b-splines with annual knots are included in the regression but not reported. All standard errors are Huber-White robust standard errors with degrees of freedom correction, and clustered at the issuer level. Model (1) uses the full range of factor scores, while model (2) truncates the factors to the range [-3,3].

	(1)	(2)
Regressors	Est.(SE)	Est.(SE)
Experience Factor	**−0.023 (0.004)**	**−0.022 (0.003)**
Connectivity Factor	**−0.026 (0.004)**	**−0.036 (0.004)**
(Constant)	2.533 (0.095)	2.540 (0.096)
Bond Buyer Index	0.031 (0.005)	0.031 (0.005)
Total Par Value (log)	−0.004 (0.003)	−0.004 (0.003)
Average Maturity Year	0.059 (0.001)	0.059 (0.001)
Percent Par Insured	0.248 (0.008)	0.248 (0.008)
Revenue Bond	0.160 (0.010)	0.160 (0.010)
Competitive Bid	−0.144 (0.007)	−0.143 (0.007)
Callable	0.523 (0.009)	0.523 (0.009)
Refunding	−0.210 (0.006)	−0.210 (0.006)
Sinking Fund	0.344 (0.007)	0.344 (0.007)
Bank Qualified	−0.215 (0.008)	−0.215 (0.008)
Taxable	0.915 (0.014)	0.916 (0.014)
Alt. Min. Taxable	0.159 (0.030)	0.158 (0.030)
Split Rating	-0.087 (0.012)	-0.088 (0.012)
Bond Rating		
AAA/Aaa	−0.806 (0.018)	−0.805 (0.018)
AA/Aa	−0.591 (0.017)	−0.590 (0.017)
A	−0.260 (0.017)	−0.259 (0.017)
BBB/Baa or below	0.422 (0.025)	0.422 (0.025)
Issuer Type		
Municipality	−0.042 (0.012)	−0.042 (0.012)
College/University	−0.120 (0.029)	−0.122 (0.029)
District	0.082 (0.012)	0.081 (0.012)
Local Authority	0.054 (0.016)	0.053 (0.016)
State Authority	0.003 (0.028)	0.000 (0.028)
State Government	−0.064 (0.024)	−0.066 (0.024)
N	74,906	74,906
R^2	0.812	0.812
Adj. R^2	0.810	0.811
AIC	119043	119014

Appendix B

APPENDIX TO CHAPTER 2

B.1 Issuer learning from experience

An additional consideration when an issuer decides which financial advisor to use for an issue is the first-hand experience of advisor quality by the issuer. Based on the results in the main body, issuers frequently return to financial advisors they have used previously. This would allow local governments to obtain first-hand experience working with the financial advisors and observing the outcomes of the bond issues they have been associated with. Learning about market fundamentals has been theorized to be a major incentive to trade in the secondary municipal bond market (Brancaccio et al., 2017). While it's unlikely that local governments would issue bonds simply to learn more about the market, they may experiment using other issuers when their recently-used advisors appear to be poor quality. Brown & Potoski (2003a) hypothesize that governments will invest in internal capacity to seek out other potential contractors when performance has been poor among their existing contractors.

We model local governments as learning a financial advisor's quality through each issue the financial advisor helps to issue for the local government. Learning occurs through Bayesian updating based on the local government's experience with the advisor. We use the results from model 3 of true interest cost presented in table 1.4 to represent the expected TIC with no prior learning. Learned TIC is an average of the difference between realized TIC and expected TIC for that combination of local government and financial advisor. This is equivalent to the expected TIC under Bayesian updating with an uninformative, flat prior. Thus, the larger the value for learned TIC, the higher the interest costs a local government would expect by working with that advisor and the lower the expected quality of the advisor. We add learned TIC to the choice model reported in 2.2.

Results are presented in table B.1. Models (1) and (2) incorporate five years' worth of learning and are consequently limited to choices made during years 2009-2016. Models (3) and (4) incorporate ten years of learning, and are therefore limited to issues after 2013 for which a full ten years of experience are available. For all models, we only use the top 20 financial advisors from each state and local governments that issued at least five bonds during the study period of 2004-2016 as those would be the advisor-issuer pairs for which there was the most learning.

The results from models (1) and (2) suggest that local governments are actually more likely to choose a poorly-performing financial advisor even after controlling for state dependence which would control for previous relationships between the local government and the advisor. In models (3) and (4) when a full ten years of experience are incorporated the relationship between learned TIC and choice becomes weaker and is no longer statistically significant. A weakly informative further weights expected TIC toward zero, but results in no meaningful difference in results.

It could be that five years is too short a time for an accurate learning baseline, and that local governments consider longer previous performance when making their choice. It's also possible that local governments weigh more recent outcomes more highly than distant ones. This latter explanation is suggested by the state dependence coefficients for this chapter which shows that more distant choices are very heavily discounted compared to recent ones. While we have not pursued this more fully here, we think it is a promising avenue for future research which could contribute to the contracting literature.

Table B.1: **Logit model of advisor choice with issuer learning.** Multinomial logistic regression of choice of financial advisor, including first-hand learning of advisor quality. Data set is limited to top 20 advisors in each state and issuers that issued at least five bonds for 2004-2016. Standard errors in parantheses.

	Dependent Variable: Chosen financial advisor			
	(1)	(2)	(3)	(4)
Experience factor	0.473^{***}	0.343^{***}	0.538^{***}	0.396^{***}
	(0.007)	(0.009)	(0.011)	(0.013)
Connectivity factor	0.399^{***}	0.343^{***}	0.361^{***}	0.307^{***}
	(0.009)	(0.009)	(0.015)	(0.015)
Exp. factor×Par	-0.003	-0.003	-0.017	-0.019
	(0.008)	(0.008)	(0.013)	(0.013)
Conn. factor×Par	-0.061^{***}	-0.063^{***}	-0.036^{**}	-0.040^{**}
	(0.010)	(0.010)	(0.017)	(0.017)
Learned TIC	0.113^{***}	0.096^{***}	0.078	0.060
	(0.032)	(0.032)	(0.050)	(0.050)
Inactive Past Year	-1.730^{***}	-1.670^{***}	-1.977^{***}	-1.908^{***}
	(0.039)	(0.039)	(0.066)	(0.066)
State Dependence				
Advisor	4.515^{***}	4.346^{***}	4.473^{***}	4.312^{***}
	(0.016)	(0.017)	(0.025)	(0.026)
Underwriter		0.360^{***}		0.391^{***}
		(0.039)		(0.066)
Indirect		1.493^{***}		1.583^{***}
		(0.055)		(0.084)
Choice Decay	0.626	0.636	0.625	0.657
	(0.034)	(0.035)	(0.058)	(0.059)
Choice Set	All	All	Top 20	Top 20
Issuers	All	All	Freq.	Freq.
Years	2009-2016	2009-2016	2014-2016	2014-2016
Num. Choices	59,709	59,709	24,054	24,054
Note:		*p<0.1; **p<0.05; ***p<0.01		

Appendix C

APPENDIX TO CHAPTER 3

C.1 Model Selection

In this section we review the model selection procedure we employed, particularly concerning three decisions - (i) whether to use a linear model (LM) or a log-linear model (LLM) of quota share prices, (ii) whether to restrict the dataset to only those quota share trades that were 'unfished' and therefore included all of the quota pounds for the transaction year, and (iii) whether to control for changes in the market over time using b-splines or quarterly and annual fixed effects.

While a number of model selection criteria exist, we focus on the root mean squared error (RMSE) of the predicted values generated using leave-one-out cross validation. For each observation i, the model is re-estimated on the dataset that excludes i. The excluded price is then estimated using the coefficient estimates from the exclusion, $\hat{P}_i^{(-i)}$. We then calculate the average deviation of the predicted value from the actual value using the formula:

$$RMSE = \sqrt{\frac{\sum_i (P_i - \hat{P}_i)^2}{N}} \tag{C.1}$$

C.1.1 Linear versus log-linear model specification

From the body of the paper, the general specification of our econometric model is:

$$\ln P_{qt} = \delta Broker + R_q' \gamma_r + \gamma_m M_q + g(t) + \varepsilon_{qt} \tag{C.2}$$

We examine whether a linear model with quota share price P_{qt} unlogged is preferred to using the logged form. We would prefer *a priori* to use the logged transformation of prices to limit the range to strictly positive values to match with economic theory as well as our data which does not contain negative quota share prices.

To begin we estimate a pooled model across all IFQ areas for each species separately using the logged and unlogged quota share prices as the dependent variable. Residual plots show evident outliers particularly for the logged form (figure C.1). Given that quota share price information is posted by brokers and well-reported in fishery news outlets, we believe these large deviations from market prices are most likely due to data entry error or unreported in-kind transfers.

We respecify the halibut model after removing any observation from the dataset for which the residual is more than four standard deviations from the predicted value. After removing the outliers, there does not appear to be any advantage between linear and log-linear functional forms based on the residual plot. While the interpretation of the estimated parameters associated with the log-linear and linear model functional forms are obviously different, they do not demonstrate any clear deviations in relative magnitude or statistical significance between the sets of estimated parameters which are reported in table C.1. The adjusted R^2 is higher for the linear models, but this is likely due to the greater variability in the data over time for the linear model compared to the log-linear specification.

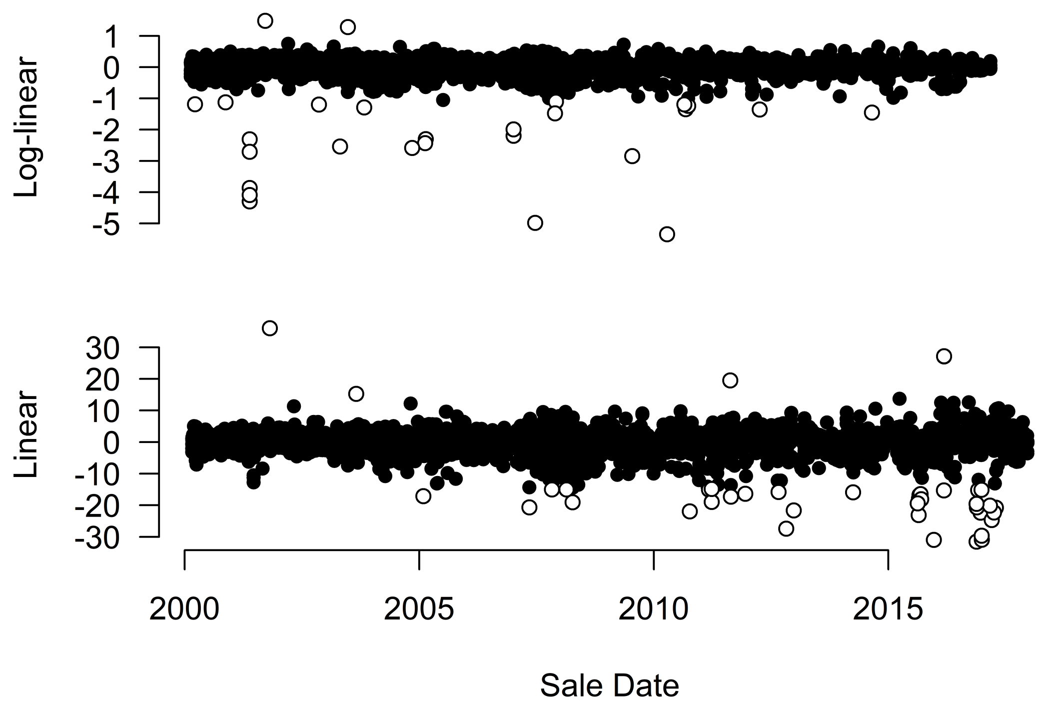


Figure C.1: Residual plot for log-linear and linear halibut quota share price models. Outliers represented by open circles.

Table C.1: Model of halibut quota share prices (price per pound) with and without outliers removed. Naive standard errors in parentheses.

	Log-linear	Linear	Log-linear	Linear
	(1)	(2)	(3)	(4)
Brokered sale	0.139***	1.579***	0.112***	1.579***
	(0.010)	(0.137)	(0.007)	(0.115)
Blocked quota	−0.116***	−2.628***	−0.128***	−2.671***
	(0.011)	(0.153)	(0.008)	(0.128)
Quota pounds in sale	0.007***	0.066***	0.006***	0.065***
(in thousands)	(0.001)	(0.008)	(0.0004)	(0.007)
Vessel Category Controls:				
Class B	−0.185***	−2.234***	−0.151***	−2.491***
	(0.042)	(0.566)	(0.029)	(0.479)
Class C	−0.160***	−1.856***	−0.151***	−2.394***
	(0.042)	(0.561)	(0.029)	(0.475)
Class D	−0.356***	−5.538***	−0.341***	−5.920***
	(0.043)	(0.569)	(0.030)	(0.482)
Time Controls:	Area-specific cubic b-splines with annual knots			
Trimmed Outliers:	No	No	Yes	Yes
Observations	4,733	4,733	4,706	4,693
Adjusted R^2	0.785	0.915	0.881	0.940
Note:				*p<0.1; **p<0.05; ***p<0.01

Residual plots for the sablefish model estimates do not show any evidence of very large asymmetric outliers for either the log-linear or linear specification. Therefore, we estimate the model without trimming any additional sablefish sales. Results of these estimates are in table C.2. As in the halibut model results, there does not appear to be any notable discrepancies between the log-linear and linear model estimates. Sablefish quota share prices display much less variability over time, and we see that adjusted R^2 is about the same for both models.

Table C.2: Model of sablefish quota share prices (price per pound). Naive standard errors in parentheses.

	Dependent variable: Sablefish quota price	
	Log-linear	Linear
	(1)	(2)
Brokered Sale	0.032^{**}	0.404^{**}
	(0.015)	(0.168)
Blocked Quota	-0.192^{***}	-2.798^{***}
	(0.013)	(0.142)
Quota pounds in sale (in thousands)	0.002^{***}	0.008
	(0.0005)	(0.005)
Vessel Category Controls:		
Class B	-0.240^{***}	-2.062^{***}
	(0.024)	(0.267)
Class C	-0.273^{***}	-2.502^{***}
	(0.025)	(0.272)
Time Controls:	Area-specific cubic b-splines with annual knots	
Observations	1,876	1,876
Adjusted R^2	0.871	0.864
Note:		*p<0.1; **p<0.05; ***p<0.01

An issue when comparing the two model specifications is that RMSE is scale-dependent. We conduct two normalizations of the root mean squared error, one based on the mean of the dependent variable and one based on the interquartile range (IQR). The normalized RMSE based on leave one out model validation is presented in table C.3. The log-linear specification is preferred under the mean-normalized calculation, but linear model is slightly preferred under the IQR normalization.

Table C.3: Normalized root mean square of errors using predicted values generated from leave-one-out cross validation.

	Halibut		Sablefish	
	Mean-Normalized	IQR-Normalized	Mean-Normalized	IQR-Normalized
Log-Linear Model	0.073	0.259	0.109	0.491
Linear Model	0.160	0.242	0.197	0.384

There are no apparent qualitative differences in model result between linear and log-linear model specifications. There is also no consistent preference for a linear model specification over a log-linear specification across any criteria. As a result, we elect a log-linear model specification going forward as more appropriate when modeling a dependent variable we expect to remain strictly positive.

C.1.2 Including fished quota

Roughly 78% of quota shares that are sold are unfished, meaning that all the quota pounds associated with those shares are included as part of the trade. This can obviously affect the transaction price since the recipient of unfished quota is receiving the additional right to catch fish in the current season as well as in subsequent seasons. Previous research has removed any fished or partially fished quota transaction to limit the market to completely homogeneous goods (Kroetz et al., 2015). While this reduces heterogeneity of quota sales, it also reduces the number of observations available to estimate the model.

We start by estimating the model both with and without fished and partially fished quota included in the dataset. For halibut, the data is again restricted to only include observations that lie within four standard deviations of the price estimates. These results appear in table C.4. The halibut estimates between the two models are very similar. Sablefish are similar, but diverge somewhat in the estimate for brokered sale. While both models estimate that brokerage use has a positive relationship with quota share price, this relationship is smaller and not statistically significant for the model that does not include partially fished quota.

Divergent estimate in the sablefish models could be partially attributable to poor fit of prices over time. We evaluate all four models again on the basis of RMSE based on predicted prices using leave-one-out cross validation. The results displayed in table C.5 clearly show that model estimates that include fished and partially fished quota share transactions are more predictive of the observed prices. For that reason, we choose to use the model that includes a fixed effect indicating the quota pounds included in the transfer.

C.1.3 Controlling for market changes over time

In order to estimate the difference in quota share prices for brokered sales compared to non-brokered sales, it is key to control for market changes over time. Previous research has controlled for market changes using seasonal and area-specific annual fixed effects (Kroetz et al., 2015). In the main paper, we use cubic b-splines with annual knots. In this section we compare the results between these two methods.

Table C.4: Model of quota share prices (price per pound) for models that include fished quota and those that do not. Naive standard errors in parentheses.

	Halibut		Sablefish	
	(1)	(2)	(3)	(4)
Brokered Sale	0.136^{***}	0.112^{***}	0.014	0.032^{**}
	(0.009)	(0.007)	(0.018)	(0.015)
Blocked Quota	-0.140^{***}	-0.128^{***}	-0.217^{***}	-0.192^{***}
	(0.010)	(0.008)	(0.015)	(0.013)
Quota pounds in sale		0.006^{***}		0.002^{***}
(in thousands)		(0.0004)		(0.0005)
Vessel Category Controls:				
Class B	-0.116^{***}	-0.151^{***}	-0.256^{***}	-0.240^{***}
	(0.037)	(0.029)	(0.032)	(0.024)
Class C	-0.124^{***}	-0.151^{***}	-0.290^{***}	-0.273^{***}
	(0.037)	(0.029)	(0.033)	(0.025)
Class D	-0.328^{***}	-0.341^{***}		
	(0.038)	(0.030)		
Time Controls:	Area-specific cubic b-splines with annual knots			
Incl. Fished Quota:	no	yes	no	yes
Observations	3,666	4,706	1,475	1,876
Adjusted R^2	0.854	0.881	0.872	0.871
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table C.5: Root mean square of errors (non-normalized) using predicted values generated from leave-one-out cross validation.

	Halibut	Sablefish
All quota	0.206	0.265
Unfished quota only	0.240	0.299

The fixed effects model is estimated for each year (y), season (s), and quota (q):

$$\ln P_{qt} = \delta Broker + R_q' \gamma_r + \gamma_m M_q + S' \beta_s + Y' \beta_y + \varepsilon_{isy} \tag{C.3}$$

The model is identical to the one in the main text except for the method for controlling for time. Instead of the b-spline function $g(t)$, we include S and Y to represent each year. S is a set of seasonal binary variables defined quarterly, with November - January comprising the off-season prior to the announce of the new catch limits, with each subsequent season defined over the following three month period. Y represents a set of year dummies to denote each of the eighteen years for which there is transaction data. In the estimates that pool across all IFQ areas, the annual fixed effects are interacted with IFQ area to create a single dummy variable for each year and IFQ area combination.

Results comparing across-area pooled model estimates for the two time controls for each species are presented below in table C.6. For halibut, we have once again removed any outlier greater than four standard deviations from the predicted value. The results are nearly identical across the two model specifications, though controlling for changes over time using b-splines results in a slightly greater adjusted R^2 value compared to seasonal and annual fixed effects.

We evaluate the two model specifications for the species-specific model as well as the area-specific models. Outliers greater than four standard deviations have once again been removed from each of the halibut models individually. Results are reported in table C.7. While the pooled halibut model shows a marginal improvement in fit for fixed effects compared to b-splines, the area-specific halibut models as well as each of the sablefish models indicate that controlling for market changes over time using b-splines produces a marginally better model fit. Because the majority of the models demonstrate a better fit using b-splines to control for change over time rather than annual and seasonal fixed effects, we use b-splines in the main paper. However, the results are nearly

Table C.6: Model of quota share prices (price per pound) for models that control for changes to prices over time using annual and seasonal fixed effects compared to b-splines. Naive standard errors in parentheses.

	Halibut		Sablefish	
	(1)	(2)	(3)	(4)
Brokered Sale	0.114***	0.112***	0.029*	0.032**
	(0.007)	(0.007)	(0.015)	(0.015)
Blocked Quota	−0.128***	−0.128***	−0.191***	−0.192***
	(0.008)	(0.008)	(0.013)	(0.013)
Quota pounds in sale	0.006***	0.006***	0.002***	0.002***
(in thousands)	(0.0004)	(0.0004)	(0.001)	(0.0005)
Vessel Category Controls:				
Class B	−0.158***	−0.151***	−0.234***	−0.240***
	(0.030)	(0.029)	(0.024)	(0.024)
Class C	−0.158***	−0.151***	−0.270***	−0.273***
	(0.030)	(0.029)	(0.025)	(0.025)
Class D	−0.345***	−0.341***		
	(0.030)	(0.030)		
Time Controls:	fixed effects	b-splines	fixed effects	b-splines
Observations	4,707	4,706	1,876	1,876
Adjusted R^2	0.875	0.881	0.866	0.871
Note:				*p<0.1; **p<0.05; ***p<0.01

identical between the two methods.

Table C.7: RMSE (non-normalized) using predicted values generated from leave-one-out cross validation for the cross-area pooled model and area-specific models using seasonal and annual fixed effects compared to cubic b-splines with annual knots.

	RMSE by model type:	
IFQ Area	Fixed effects	b-splines
All Halibut	0.204	0.206
2C	0.179	0.174
3A	0.204	0.200
3B	0.363	0.354
4A	0.178	0.175
All Sablefish	0.283	0.264
SE	0.262	0.153
CG	0.265	0.262

Appendix D

APPENDIX TO CHAPTER 4

D.1 Random Bidding Model Distribution

Here we adapt the discussion in Lerman & Kern (1983) to the case where the scale parameter is not equal to one. We define x as equal to the maximum of M draws, where each draw is indexed by i from a generalized extreme value 1 (denoted GEV1) distribution with location parameter zero and scale parameter σ.

$$\begin{aligned} x &:= \max_i \varepsilon_i, \text{ where } \varepsilon_i \sim GEV1(0,\sigma) \\ &= \max_i \sigma u_i, \text{ where } u_i \sim GEV1(0,1). \end{aligned} \tag{D.1}$$

Taking the natural log of the probability that $\max_i \varepsilon_i$ is less than X:

$$\ln Pr(x < X) = \ln \prod_i (u_i\sigma \leq X) = \sum_i \ln Pr(u_i \leq \frac{X}{\sigma}) \tag{D.2}$$

From the definition of the extreme value type-I distribution:

$$\begin{aligned} \ln Pr(x < X) &= \sum_i^M \ln exp(-exp(\frac{X}{\sigma})) \\ &= \sum_i^M -exp(-\frac{X}{\sigma}) = -exp(-\frac{X}{\sigma})M \\ &= -exp(-\frac{X}{\sigma} + \ln(M)) = -exp(\frac{-X+\sigma\ln(M)}{\sigma}) \end{aligned} \tag{D.3}$$

Which is equivalent to the natural log of the cumulative distribution function of the extreme value type-I distribution, with location parameter $\sigma \ln(M)$ and scale σ. The mean of the extreme value type-I distribution is the location plus the Euler-Mascheroni constant all multiplied by the scale, $\sigma \ln(M) - \sigma\Gamma'(1)$.

D.2 Alternative broker bid-gathering rates

In order to identify the random bidding model, we assume a broker bid-collection rate of 3%. In figure D.1 below, we display differences between an assumed rate of 3% and assumed rates of 1% (black) and 10% (gray). There are few differences between the estimates, and none that impact the inferences that we make about willingness-to-pay across bidder categories.

Unsurprisingly, adjusting the bid-collection rate of brokered trades changes the estimated rate at which bids are collected through non-brokered means. As broker bid-collection rates increases, so too does the assumed baseline non-brokered collection rate. As this baseline rate increases, it decreases the estimated impact of city size on non-brokered data collection. The estimated coefficient for city size at a 10% rate is roughly the same as 3%, but the coefficient for the 1% rate is somewhat greater for area 2C and considerably greater for 3A.

The only coefficient directly relating to willingness-to-pay that is changed due to change in assumed bid-collection rates is the intercept. As bid-collection rates increase, the baseline willingness-to-pay is assumed to be lower as the seller is assumed to be maximizing price over an increasing number of bids. However, the implied scale of the distribution of willingness-to-pay (denoted by 'invsigma') and the estimates of bidder categories remain invariant to assumed bid-collection rate. We do not display other time-varying controls in the figure, but those remain unchanged as well.

Figure D.1: Coefficients for random bidding model under alternative assumed broker bid-gathering rates. Black represents the difference in z-score of the estimate between an assumed collection rate of 1% and 3%, while gray represents the z-score difference for rates of 10% and 3%.

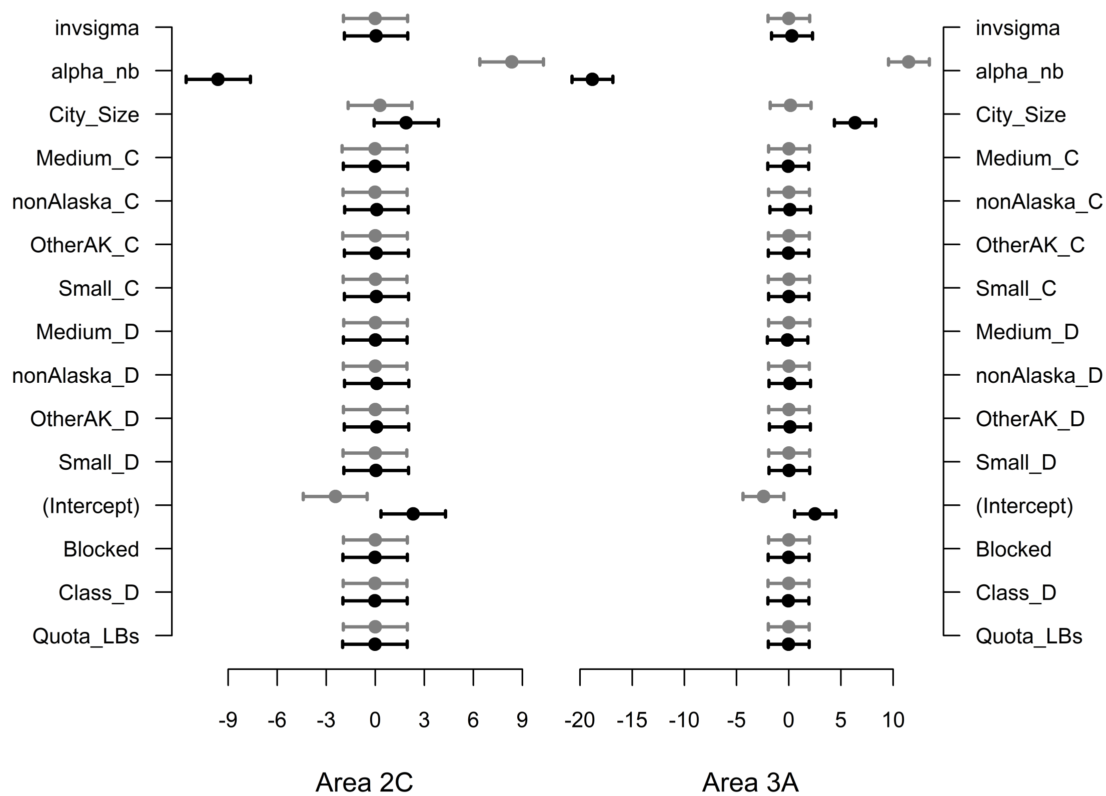
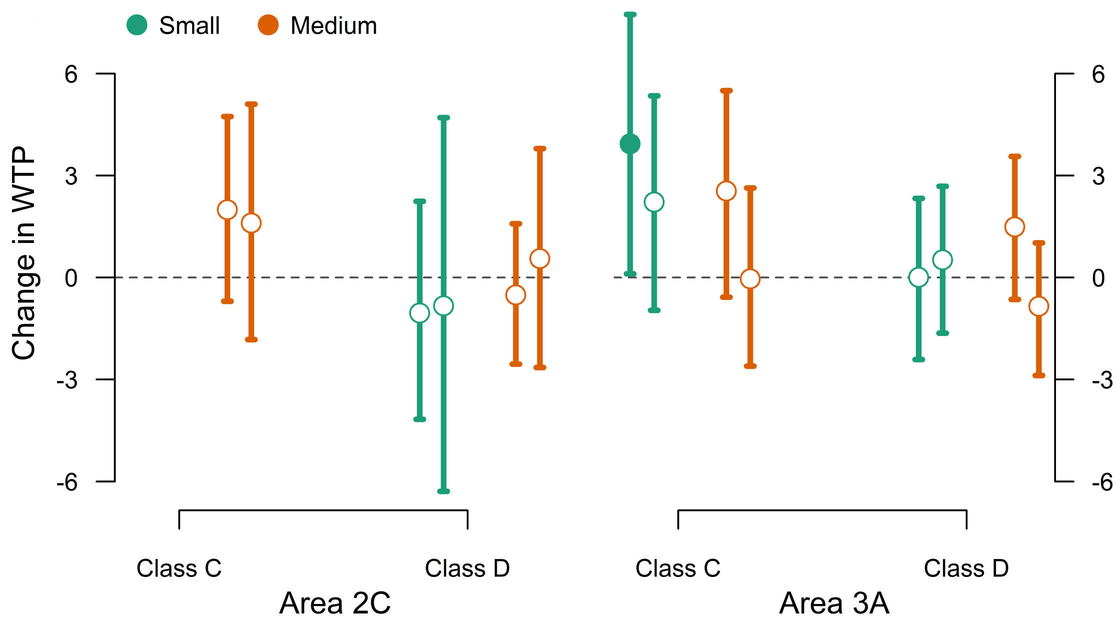


Figure D.2: Placebo estimates to change in willingness-to-pay for 2012 and 2013, relative to bidders in large communities.



D.3 Regression discontinuity model placebo tests

In this section we report the results of regression discontinuity models that were estimated using false policy date thresholds for the GAF policy implementation, commonly known as placebo tests. We select cutpoints during each of the two years leading up to the GAF policy as our placebo thresholds due to their proximity to the true policy implementation date and because changes in total allowable catch (TAC) for 2C and 3A were similar in 2012 and 2013 as in 2014. In 2012 the TAC was increased for area 2C by 0.29 million pounds, and in 2013 by 0.35 million pounds, the TAC increased by 0.35 million pounds again in 2014 at the same time the GAF program was announced. Similarly, the TAC decreased in area 3A in 2012 by 2.44 million pounds and 0.89 million pounds in 2013, which is somewhat less than the 2014 decrease in TAC of 3.7 million pounds in area 3A.

One of the placebo estimates rises to the level of statistical significance, which casts some possible doubt as to the internal validity of the results presented in the main body. However, only one estimate rises to the level of statistical significance out of 14 total possible combinations, and even this one estimate is only marginally statistically significant, which provides some measure of reassurance of the validity of the regression discontinuity results in the main body of the paper.

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