Estimating willingness-to-pay for fishing quota using a random bidding model

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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.[1] 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

[1] To illustrate this more formally, I 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.

relationship between quota pound price and quota share price (Jin et al., 2019; Newell et al., 2005, 2007).

However, price dispersion is an empirical feature of many quota markets, including the Alaska halibut quota share markets, implies a distribution of willingness-to-pay for quota shares among fishery participants. It can be valuable to estimate the distribution of willingness-to-pay, particularly when evaluating a policy change that may have distributional consequences. In this paper, I 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. I 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.

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, 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).

2 Random Bidding Model

2.1 Background and model overview

Rather than a linear model of prices as has been done previously in the literature, I 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 I apply this method to later is a commercial fishery, profit-maximization appears to be a reasonable assumption[2] 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

[2] 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.

with selling to a particular individual or by a specific method of sale. Instead, I 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 zero until or unless quota is sold through the broker, I 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.

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:

$$wt\,p_{qikt} = \psi_{qkt} + \varepsilon_{qikt}. \tag{1}$$

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):

$$\max\{\psi_{qik^*t} + \varepsilon_{qik^*t}\} > \max\{\psi_{qikt} + \varepsilon_{qikt}\} \forall k \neq k^*. \tag{2}$$

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.[3]

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, I assume

[3]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.

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. I assume brokerage affects the bid value through the number of bids the seller receives, rather than the underlying 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:

$$\psi_{k^*} + \sigma \ln(M_{qs^*k^*}) + \varepsilon_{qs^*k^*} > \psi_k + \sigma \ln(M_{qsk}) + \varepsilon_{qsk} \; \forall \; \{k,s\} \neq \{k^*, s^*\}. \tag{3}$$

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, I 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. I denote sale price P_q^*, for the winning bid from type k^* and method s^*:

$$P_q^* = \psi_{k^*} + \sigma \ln(M_{qk^*s^*}) + \varepsilon_{qk^*s^*}. \tag{4}$$

Substituting and rearranging equations (3) and (4), the probability density and the cumulative density functions of the random error are defined by

$$\begin{aligned} \varepsilon_{qk^*s^*} &= P_q^* - \psi_{k^*t} - \sigma \ln(M_{qk^*s^*}) \\ \varepsilon_{qks} &< \tilde{P}_q^* - \psi_{kt} - \sigma \ln(M_{qks}) \; \forall \; \{k,s\} \neq \{k^*, s^*\} \end{aligned} \tag{5}$$

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, I 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:

$$
\begin{aligned}
Prob_q(Y_{k^*s^*}) &= f_e(P^* - \psi_{k^*} - \sigma \ln(M_{k^*s^*})) \prod_{ks \notin k^*s^*} F_e(\tilde{P}^* - \psi_k - \sigma \ln(M_{ks})) \\
&= \frac{1}{\sigma} e^{-\frac{1}{\sigma}[P^* - \psi_{k^*} - \sigma \ln(M_{k^*s^*})]} exp\{-e^{-\frac{1}{\sigma}(\tilde{P}^* - \sigma \ln \sum_{k,s} exp\{\frac{1}{\sigma}[\psi_k + \sigma \ln(M_{ks})]\})}\},
\end{aligned}
\tag{6}
$$

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, I 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. I draw on the literature concerning probabilistic choice sets to formulate our model, specifically I 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, I 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:

$$\rho_{qks} = \frac{1}{1+e^{-\alpha_s - \lambda_s' w_{qk}}}, \tag{7}$$

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:

$$Prob(M_{qks} \geq 1) = \frac{1-(1-\rho_{qks})^{N_k}}{1-\Pi_{k,s}(1-\rho_{qks})^{N_k}}, \tag{8}$$

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:

$$Prob_q(Y_{ks}) = Prob_q(Y_{ks}|M_{ks} \geq 1) \times Prob_q(M_{ks} \geq 1), \tag{9}$$

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 (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:

$$E[M_{qk^*s^*}] = E[M_{qks}|M_{qks} \geq 1] = \frac{\rho_{qks}N_k}{1-(1-\rho_{qks})^{N_k}}. \tag{10}$$

The log likelihood of the full unconditional probability defined in equation (9) of observing a quota sale to bidder type k using sale method s is defined as:

$$\begin{aligned} \mathbb{L} = N\ln\sigma - \frac{1}{\sigma}\sum_q [P_q^* - \psi_{k^*} - \sigma\ln(E[M_{qk^*s^*}])] - \sum_q\sum_{k,s} e^{\frac{1}{\sigma}(\psi_k+\sigma\ln(E[M_{qks}])-\tilde{P}_q^*)} \\ + \sum_q \{\ln[1-(1-\rho_{qk^*s^*})^{N_k^*}] - \ln[1-\prod_{ks}(1-\rho_{qks})^{N_k}]\}. \end{aligned} \tag{11}$$

3 Application

I 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.

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

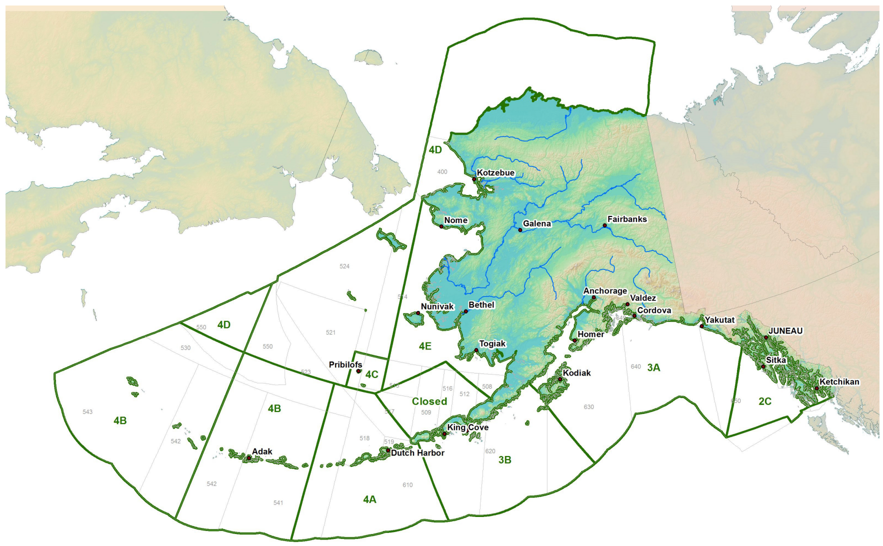


Figure 1: **Halibut Quota Management Areas** reprinted from (NOAA, 2019a)

determined by the North Pacific Fishery Management Council for each of the eight management areas (figure 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. Information on the Alaskan halibut IFQ policy is available in (Hayes, 2019), and has appeared elsewhere in government reports (NOAA Fisheries, 2015; NMFS, 2016) and the academic literature (Kroetz et al., 2015; Szymkowiak & Himes-Cornell, 2015).

I 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; Smith, 2005), and population adjacent to the IFQ area is thought to influence quota demand (Szymkowiak & Himes-Cornell, 2015). For that reason, I 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, I 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.

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 each 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. Under economically efficient fishery policies in both the recreational and commercial sector, 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, I also estimate the impact of GAF on willingness-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.

3.2 Model Specification

I 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. The dependent variable is estimated using a log-transformation in order to restrict predicted prices to positive values:

$$\ln(\psi_{qkt}) = g_t + R_q'\gamma_r + I_{k\times vessel}'\beta_{k\times vessel}. \tag{12}$$

I estimate non-brokered bid-collection rate, ρ in equation 7, as a function of the potential social network available to the seller. Hayes (2019) shows that buyers and sellers who engage in non-brokered trades tend to live in the same city, deliver catch to the same ports, and/or sell catch to the same processor, implying a greater ability for sellers to collect bids from those with whom they share these ties. The number of bidders of type k that share these attributes with the seller represent the three relational variables used as w_{qk} in equation 7. Given that brokers advertise throughout the entire quota market, I 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 I 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 underlying willingness-to-pay by bidder type, I identify the model by setting α_{broker} equal to the arbitrary value of 3%. This allows the other parameters to be estimated and does not appreciably affect the parameter estimates. Robustness checks that re-estimate the model under a variety of α_{broker} values find this choice appreciably impacts few parameter estimates.[4]

$$\begin{aligned} \rho_{qks} &= \frac{1}{1+e^{-\alpha_s-\lambda_s' w_{qk}}}, \text{ for } s = nonbroker \\ \rho_{qks} &= 3\%, \text{ for } s = broker \end{aligned} \tag{13}$$

3.3 Data

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, 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.

I limit the transfer report price data to trades that are arms-length and for which consistent price data can be calculated. The focus is particularly 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

[4]This choice consistenly impacts the magnitude of the $\alpha_{nonbroker}$ parameter estimate in the bid-collection sub-model and λ_s, the intercept term for the common time-varying component in equation 12. For some values of α_{broker}, the relational parameters in the bid-collection sub-model may be impacted as well. The appendix contains parameter estimate comparisons under assumptions of 1% and 10% rate.

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, there are 1345 remaining 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, I rely on address information provided by AKFIN. Particularly, the city and state of each potential bidder is geocoded, and this geocode is used to define whether the bidder's community is located adjacent to the IFQ area in question. I define any Alaskan 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, I only use quota holdings database to define the set of eligible bidders.

I use the name of the city to match to census information for year 2010 to obtain the population for each Alaskan city.[5] Using Carothers et al. (2010) for guidance, I 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.[6] Communities for each area and size appear in table 1.

Data on a seller's home city is also incorporated in the bid-gathering sub-model defined in equation

[5]I 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 I judged the added value of this approach to be insufficient to justify the imputation procedure here.

[6]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. I 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 1: List of Alaskan communities by size category, adjacent to areas 2C and 3A.

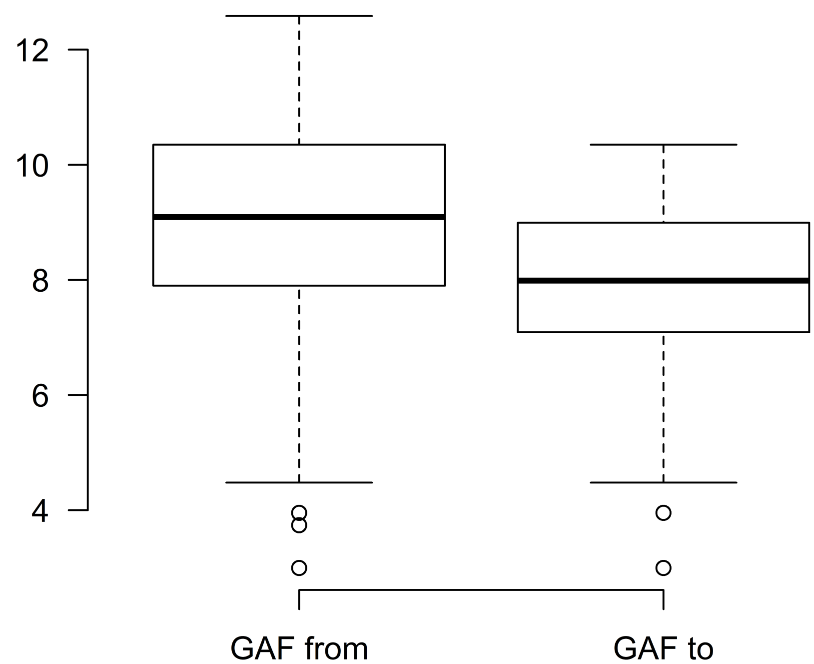
	Area 2C	Area 3A
Large	Ketchikan, Juneau, Sitka	Anchorage, Wasilla
Medium	Haines, Petersburg, Wrangell	Anchor Point, Big Lake, Cordova, Fritz Creek, Homer, Kenai, Kodiak, Nikiski, Palmer, Seward, Soldotna, Sterling, Valdez, Willow
Small	Angoon, Coffman Cove, Craig, Edna Bay, Elfin Cove, Gustavus, Hoonah, 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

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. I 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. Count data is transformed using the inverse hyperbolic sine method[7] due to high skewness and large outliers in the data, as well as a large number of zeroes. In addition, I 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 commercial sector, I 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

[7] Inverse hyperbolic sine 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.

Figure 2: Logged origin and destination community populations for quota transfers under the GAF program.



smaller ones. Figure 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 Results

Model estimates for area 2C appears in table 2 and estimates for area 3A appears in 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 3 and 4.

Table 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 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

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.[8]

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 3 and 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 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 the researcher 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, I 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 differ-

[8]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.

Figure 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 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.

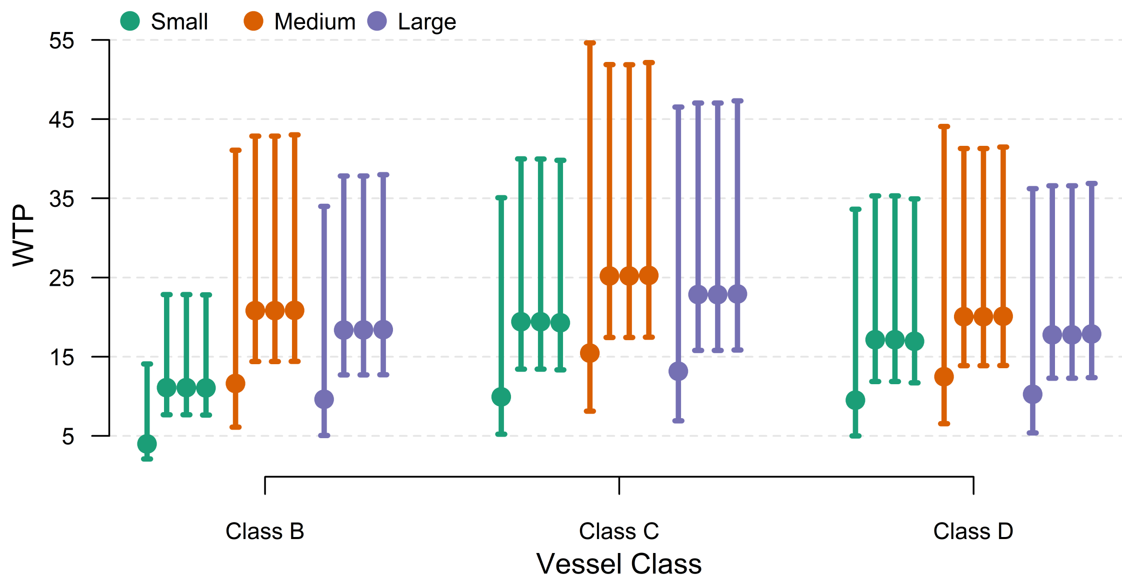
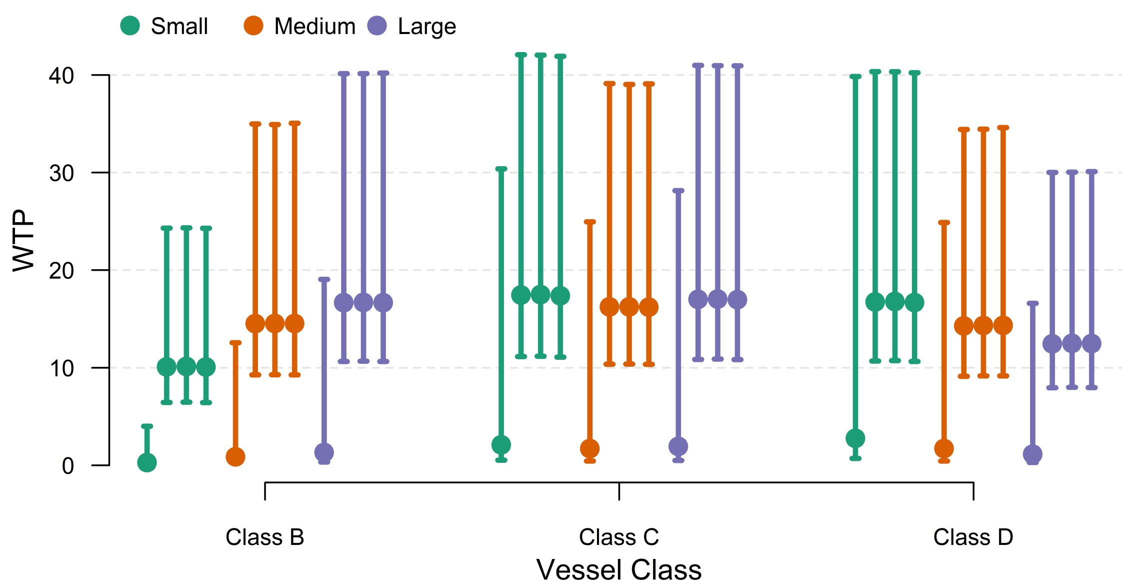


Figure 4: Point estimate of distribution of willingness-to-pay for bidders from small, medium, and large communities based on models (1)-(4) reported in Table 3. The median is represented by the point and the middle 95% of the distribution represented by the line. Willingness-to-pay is based on unblocked quota and no quota pounds sold on January 1, 2016.



ence between the model formulations that use the IHS transformation and binary representation 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, I 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 5 and 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 communies. In area 3A, I 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 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%.

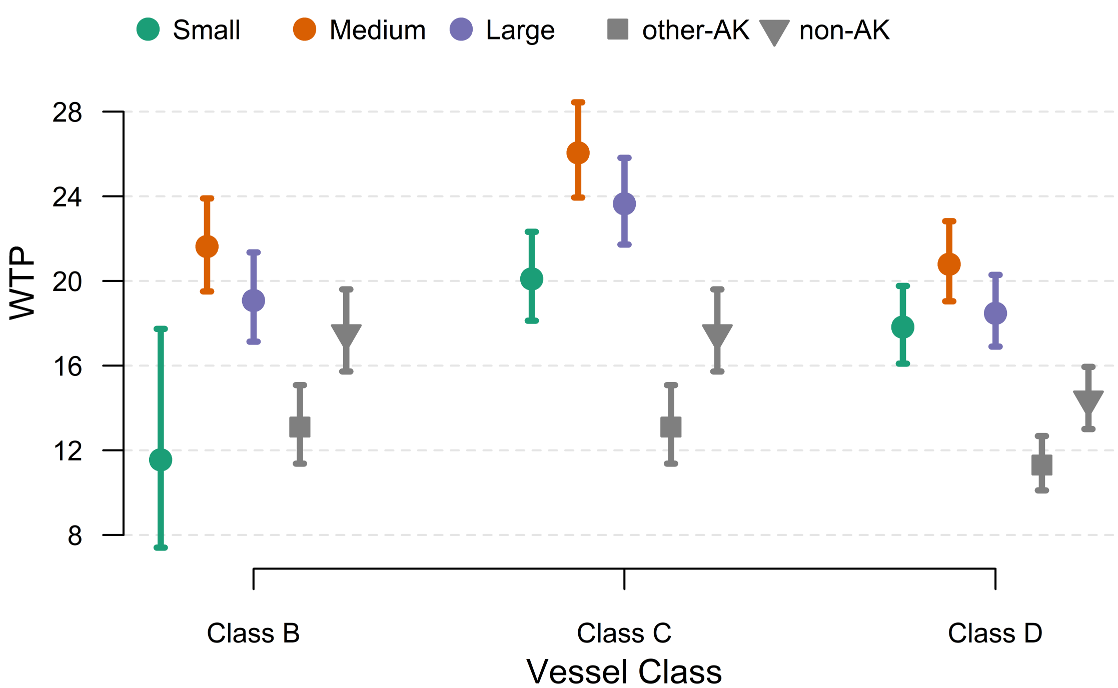
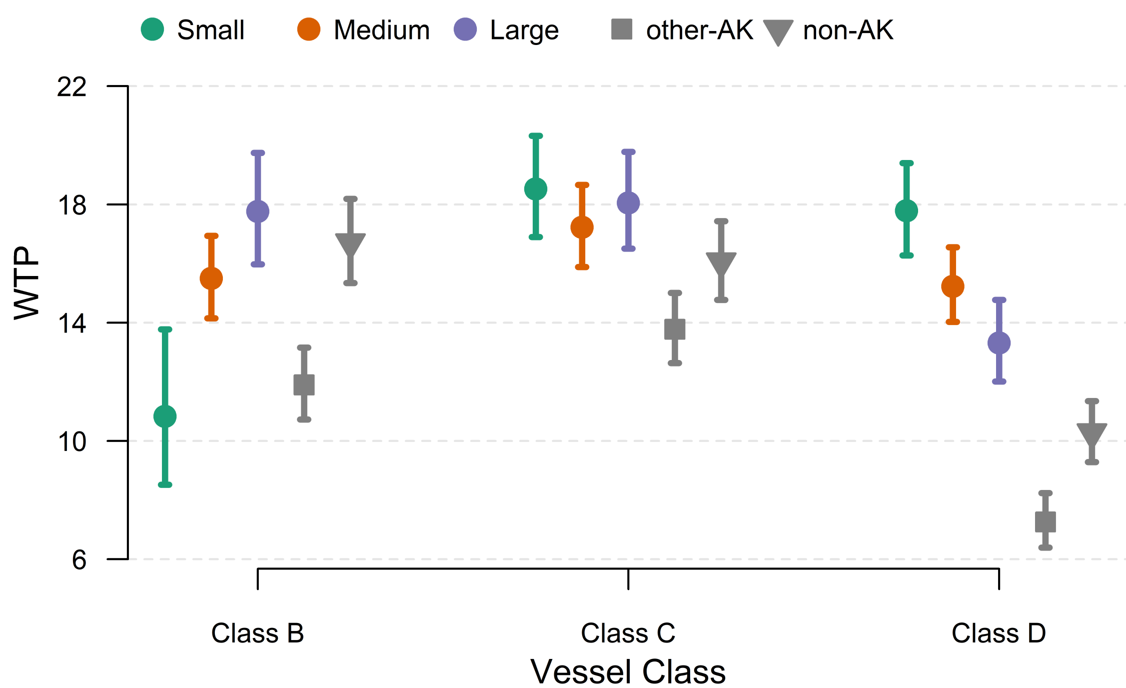


Figure 6: Estimated mean willingness-to-pay for area 3A quota across five bidder types; bidders adjacent to the IFQ area residing in small, medium, and large communities, bidders from Alaska but not adjacent to the area (Other-AK), and bidders from outside of Alaska (non-AK).The WTP estimate is applied here to unblocked quota sale with no quota pounds as of January 1, 2016 and assuming a brokered bid collection rate of 3%.



4.1 GAF model and results

To test for the effect of the GAF transfer program on willingness to pay, I use a regression discontinuity design.[9] Regression discontinuity is a quasi-experimental method in which causal inferences are drawn based on a discontinuous change in policy at some defined threshold. I 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, I exclude class B data from our estimates. Our estimation procedure remains largely the same as described above. I again estimate a willingness-to-pay based on equation 1. However, I define an alternative specification for ψ_{qkt} as a local linear model:

$$\psi_{qkt} = R_q'\gamma_r + \theta_1 I_{t>0} + \theta_2 t + \theta_3 t I_{t>0} + I_{k\times vessel}'\beta_{0,k\times vessel} + I_{t>0} I_{k\times vessel}'\beta_{1,k\times vessel} \tag{14}$$

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, I 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), I use a local linear approach rather than a global polynomial to control for changes over time. I 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

[9] 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 I could identify a proper counterfactual using an IFQ area outside 2C and 3A.

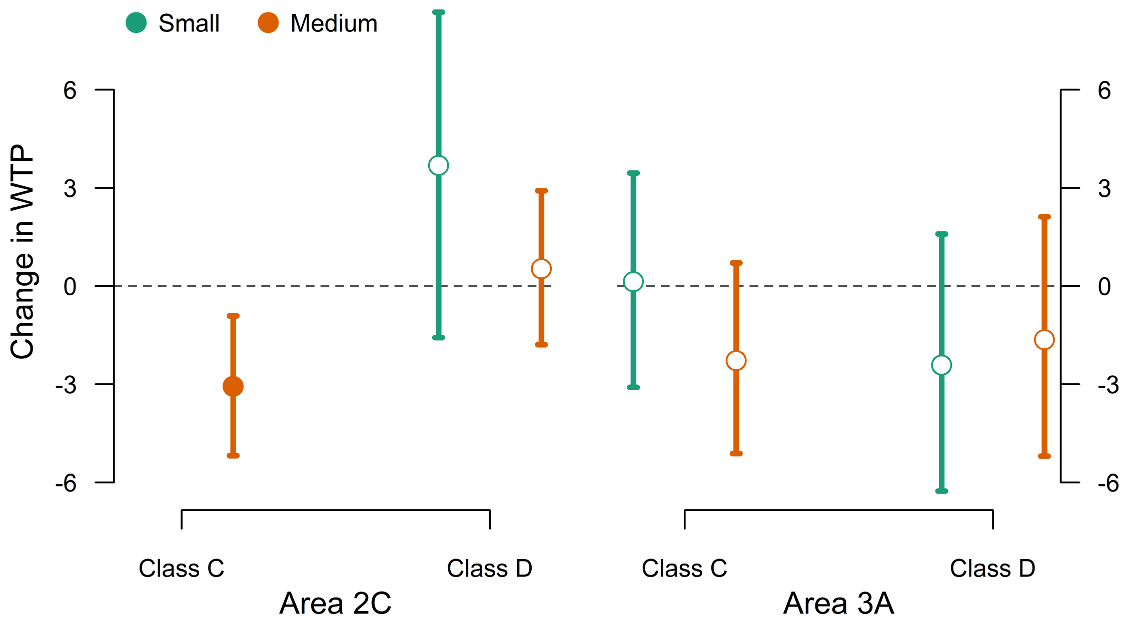
2.07 years and 2.64 years of the GAF policy implementation on January 13, 2014 will be included in area 2C and area 3A estimates, respectively. Finally, I weight the observations in the model using a triangular kernel, disproportionately weighting sales that occur near the discontinuity.[10] Both the bandwidth and weighting calculations are conducted using the rdd package in R (Dimmery, 2016).

I 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 I only report the relative changes to willingness-to-pay for groups as compared to a reference category. In particular, I 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 I 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 7. They suggest that willingness to pay among bidders from small communities did not decline more than willingness-to-pay among bidders from large communities 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

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

Figure 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.



a result, I am 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.

5 Discussion and conclusion

I 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, I 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 I 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, I think this method would be valuable in evaluating the distributional impacts of policies. In this example, I 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, I 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, I 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. I did not find any evidence that allowing quota transfers to the for-hire sector particularly disadvantaged harvesters from small communities. However, I 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, I 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.

I 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, I do not consider heterogeneity among sellers. For instance, I 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 I 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, I 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.

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Appendix A 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.

$$\begin{aligned} x &:= \max_i \varepsilon_i, \text{ where } \varepsilon_i \sim GEV1(0,\sigma) \\ &= \max_i \sigma u_i, \text{ where } u_i \sim GEV1(0,1). \end{aligned} \tag{15}$$

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

$$\ln Pr(x < X) = \ln \prod_i (u_i \sigma \leq X) = \sum_i \ln Pr(u_i \leq \frac{X}{\sigma}) \tag{16}$$

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

$$\begin{aligned} \ln Pr(x < X) &= \sum_i^M \ln exp(-exp(\frac{X}{\sigma})) \\ &= \sum_i^M -exp(-\frac{X}{\sigma}) = -exp(-\frac{X}{\sigma})M \\ &= -exp(-\frac{X}{\sigma} + \ln(M)) = -exp(\frac{-X + \sigma \ln(M)}{\sigma}) \end{aligned} \tag{17}$$

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, $\sigma \ln(M) - \sigma \Gamma'(1)$.

Appendix B Alternative broker bid-gathering rates

In order to identify the random bidding model, we assume a broker bid-collection rate of 3%. In figure 8 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 8: 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%.

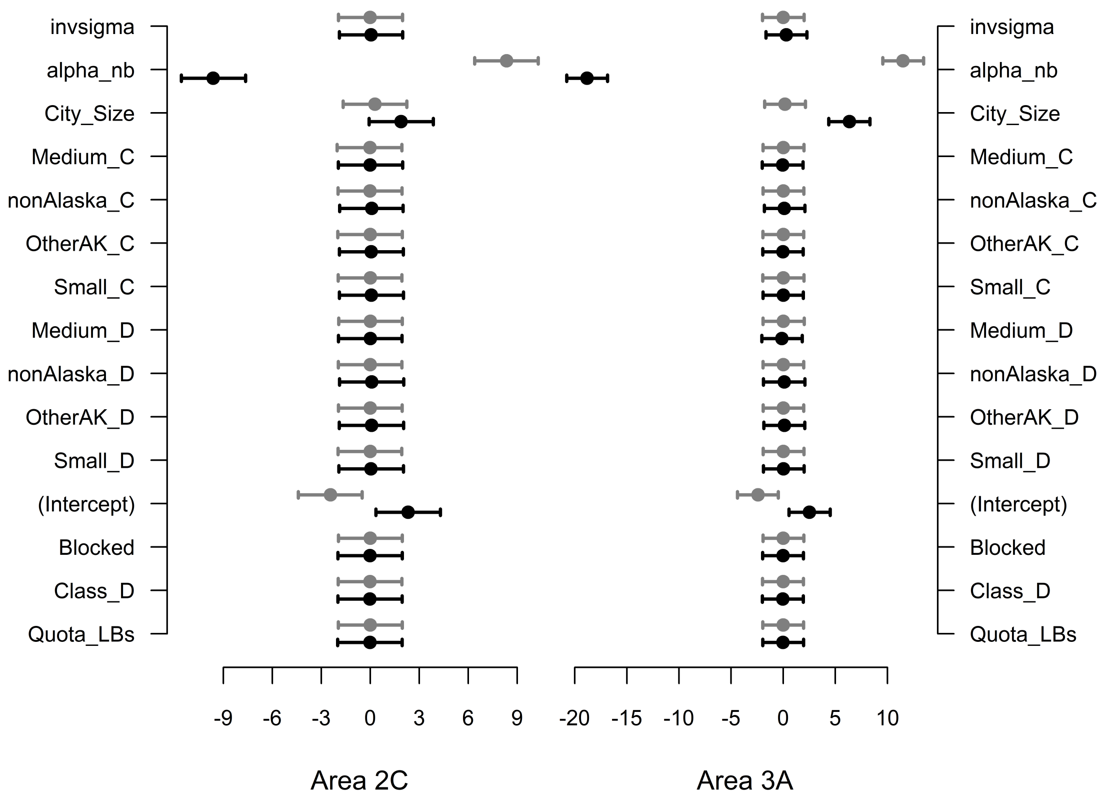
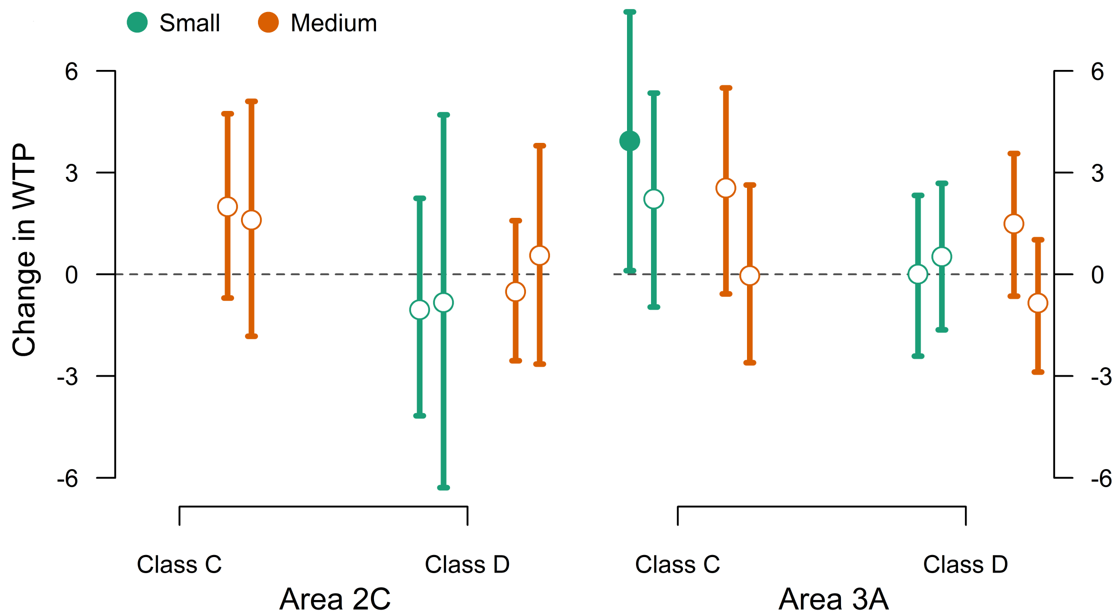


Figure 9: Placebo estimates to change in willingness-to-pay for 2012 and 2013, relative to bidders in large communities.



Appendix C 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.