APPENDIX: UNRAVELING THE MULTIPLE MARGINS OF RENT GENERATION FROM INDIVIDUAL TRANSFERABLE QUOTAS

I. DATA SOURCES

Our descriptive analysis of the RKC fishery and the calibration of our crab harvesting conceptual model draws upon multiple rich and detailed pre- and post-ITQ data sets, the details of which are the focus of this section.

Confidential Skipper Interviews

The Alaska Department of Fish and Game (ADF&G) Shellfish Observer Program conducts confidential skipper interviews for the purpose of acquiring information about daily fishing activities over the course of a fishing trip.[1] Interviews are conducted either onboard a vessel or dockside after the skipper's arrival at a processor. Data from the interview is recorded on two forms: the Confidential Interview Form (CIF) and the Confidential Interview Summary Form (CIF Summary).

The CIF is a daily account of fishing effort and catch by string of gear over the course of a fishing trip. The CIF includes variables such as the date fished, the statistical area in which

[1] A detailed discussion of the Confidential Interview, along with example interview forms, can be found in the ADF&G Shellfish Observer Program's Crab Observer Training and Deployment Manual: ftp://ftp.afsc.noaa.gov/afsc/public/crab/2008_Shellfish_Observer_Mannual_Chap_5_Confidential-Interviews.pdf.

crab were caught, the number of crabs retained for the entire string, the total number of pots lifted in each string, the average soak time for each string, and the average depth of all pots in a string. The CIF Summary is used to summarize select information from the CIF, as well as to record information from the vessel's delivery. Variables contained in the CIF Summary include the beginning and end dates of a trip, the number of strings in a trip, the number of days fished (i.e. days in which gear was set and/or pulled) over the course of the trip, and the amount of offload deadloss incurred by a vessel at the end of a trip.

Observers deployed on a vessel complete one CIF data set per trip. Interviews are conducted and an entry is made each day, regardless of the existence of any fishing activity. Vessels that do not have an observer onboard participate in interviews conducted at dockside at the end of a trip. Importantly, the ADF&G Shellfish Observer Program does not require 100% coverage, meaning that not all vessels are required to carry an observer at all times. Further, a vessel without an observer will not necessarily be interviewed dockside at the end of a trip.[2] Thus, CIF data is not comprehensive over all trips, and therefore, expansion of trip data to the seasonal level is unsupported.

Fish Tickets

A fish ticket (or E-landing) is a State of Alaska required record of purchase between a fishing vessel and a processor. Fish tickets are handled by the ADF&G and play an important role in fisheries management.[3] The fish ticket data set used in this paper is a comprehensive collection of all formal transactions taking place between catcher vessels and processors, and includes

---

[2] Vessels are selected with some probability to participate in a Confidential Interview when they arrive at a processor at the end of a trip. We assume for this study that the selection process occurs randomly; however, there is little information on whether or not an exact protocol exists to ensure random selection is achieved.

[3] For more information on fish tickets (or E-landings), see https://elandings.alaska.gov/.

information such as the delivery date, species landed, delivery weight, deadloss weight, catch dates, and value of the delivery. We exploit the comprehensive nature of the fish ticket data set to substitute for CIF data when summarizing certain variables over the course of a season.

Economic Data Reports

As part of the rationalization process of the RKC fishery, vessel owners were mandated to file annual Economic Data Reports (EDR). The data collected by EDRs includes annual revenue from landings of targeted species, information on labor contracts of captain and crew, payments to crewmembers, and many other operating costs. A particular useful feature of the mandated EDR data collection effort was the required provision of historical data for select pre-ITQ years (1998, 2001, and 2004) by all vessels that participated in the pre-ITQ fishery.[4]

While the EDR data set provides a unique opportunity to compare performance measures between years before and after ITQ implementation, EDR data collection is somewhat compromised by inconsistency and poor quality of some data series. In particular, there as been tension between refining the survey to better extract desired information while maintaining comparability of the resulting data through time. Due to the industry's influence in defining the appropriate use of the EDR data, an extensive data audit was conducted, resulting in a thorough description of the data and provision of guidelines and limitations as to how the data should be used.[5] We are mindful of these limitations in our use of the EDR data to calibrate our conceptual model, the exact details of which are discussed later in this Appendix.

---

[4] Abbott, Garber-Yonts and Wilen (2010) use the EDR data extensively in their analysis of employment and remuneration before and after ITQ implementation in the both the red king crab and snow crab fisheries.

[5] Full documentation for the EDR database, in the form of a metadata document, along with a Data Quality Summary document resulting from the data audit, can be found on the National Marine Fisheries

II. NUMERICAL METHODS

The complicated nature of the harvester's production process developed in Section III results in a joint maximization and fixed-point problem [15] that does not have an analytical solution. Thus, we use numerical methods to find a representative harvester's best response to the actions of other harvesters and solve for a SNE. In addition, we use calibration techniques so that the behavioral model in Section IV mimics the 2004 conditions of the RKC fishery. The algorithm for the calibration and numerical techniques used in this paper is depicted in Figure A1 and described in the sections that follow.

Best Response Function

A harvester's best response function $\Lambda : \Re_+^{4(\eta-1)} \rightarrow \Re_+^4$ to the actions of all other harvesters Λ_{-i} is the solution to the maximization problem in [15]. This maximization problem is complicated by the fact that the choice variable t is discrete, making the maximization problem a Mixed Integer Nonlinear Programming (MINLP) problem, which refers to mathematical programming with continuous and discrete variables and nonlinearities in the objective function and constraints.[6]

While MINLP problems are notoriously difficult to solve, the nature of problem [15] fortunately allows us to avoid most of the extra complications that arise with MINLP problems. First, there is only one discrete choice variable t, reducing the complexities associated with combining combinatorial optimization—in which the set of feasible solutions is discrete in multiple dimensions—and continuous optimization. Second, although the discrete choice variable t can take the value of any positive integer, the economically feasible set of trips is actually quite small. Diminishing marginal returns to an additional trip—due to the concavity of

---

Service's Alaska Regional Office website: http://www.fakr.noaa.gov/sustainablefisheries/crab/rat/edr/default.htm.

[6] Grossmann (2002) provides a good overview of solving MINLP problems.

the crab deterioration function $\rho(\cdot)$ in equation [10], combined with a fixed cost c^t for embarking on an additional trip—implies that the number of trips chosen will not be much (if at all) larger than the minimum number of trips needed to satisfy the hold capacity constraint. In reality, the majority of harvesters in both the pre- and post-ITQ RKC fishery embark on no more than three trips within a season. Thus, in a properly calibrated model, we expect that our numerical algorithm will have to search over very few values of t.

Finding the best response function can therefore be described by the following algorithm (Figure A1c), where we let $(t,\Lambda_{-i}) \mapsto V(t,\Lambda_{-i})$ and $(t,\Lambda_{-i}) \mapsto \Phi(t,\Lambda_{-i})$, denote the value and demand functions, respectively, that are obtained from maximizing the objective function in [15] with respect to d, v, and N for a given value of $t \in \mathbb{N}$ and actions of all other players $\Lambda_{-i} \in \Re_{+}^{4(\eta-1)}$. First we obtain $V(t = 1, \Lambda_{-i})$ and $\Phi(t = 1, \Lambda_{-i})$ through constrained optimization using the penalty function method. That is, we convert the constrained optimization problem in [15] into an unconstrained maximization problem by adding penalties to the objective function for violating the constraints.[7] Second, we evaluate $V(t =2, \Lambda_{-i})$ and compare it to $V(t = 1, \Lambda_{-i})$. If $V(t = 1, \Lambda_{-i}) > V(t = 2, \Lambda_{-i})$, then diminishing returns to t ensures that a harvester will certainly not embark on more than one trip, resulting in a best response of $\Lambda(\Lambda_{-i}) = [\Phi(t = 1, \Lambda_{-i}), 1]$. In contrast, if $V(t = 2, \Lambda_{-i}) > V(t = 1, \Lambda_{-i})$, then we evaluate $V(t = 3, \Lambda_{-i})$ and compare it to $V(t = 2, \Lambda_{-i})$, proceeding in similar fashion to the previous argument until we find the best response $\Lambda(\Lambda_{-}$

[7] See Judd (1998) for more details concerning the penalty function method for numerical constrained optimization. Numerical maximization of the penalty function is achieved through the use of MATLAB's built-in fminsearch command, which uses the simplex search method of Lagarias et al. (1998). Essentially, the simplex method is a direct search algorithm that does not require numerical or analytical gradients. This is a nice feature for our model since gradient methods may converge to nonoptimal solutions due to the nonconvexity of the production technology. The simplex method may still only find local solutions, however, so caution must still be exercised when looking for a maximum to problem [15].

$_i$). With well-chosen parameter values, this algorithm rarely requires more than two evaluations of $V(\cdot)$, depending on the number of players η.

Finding the Symmetric Pure Strategy Nash Equilibrium

We know that the symmetric equilibrium actions of all players in a symmetric game will be the same, so we let $\Lambda_{-i} = [d_{-i}, v_{-i}, N_{-i}, t_{-i}]$, reducing the dimension of the domain of the best response function from $4(\eta - 1)$ to 4. Then a SNE is a value of Λ_{-i} such that

$$\Lambda(\Lambda_{-i}) - \Lambda_{-i} = 0 \qquad \text{[A1]}$$

which can be solved using any standard root-finding method, or equivalently, by minimizing the distance function $\left[\Lambda(\Lambda_{-i}) - \Lambda_{-i}\right]'\left[\Lambda(\Lambda_{-i}) - \Lambda_{-i}\right]$, which is the method we employ (Figure A1b). Note that finding the solution to equation [A1] shares similar difficulties as the maximization problem in [15] due to the discreteness of t. We handle this in similar fashion to finding the best response function by solving equation [A1] with respect to d, v, and N over the small economically feasible set of $[t, t_{-i}]$. In general, we are not guaranteed that an SNE is unique, if an SNE exists at all. To check for the uniqueness of a SNE, we solve equation [A1] using many different starting values. If multiple SNE exist, we choose the SNE that provides the highest equilibrium payoffs for all players. This is a common strategy for selecting between multiple Nash equilibria and is typically motivated by Schelling's (1960) focal point refinement of Nash equilbria.

III. MODEL CALIBRATION

This section describes the calibration methods used for the model developed in Sections III and IV (Figure A1a). While estimating our structural parameters from an econometrically specified model would be ideal, reality prevents us from doing so. In fact, many of the endogenous micro-decisions we have chosen to include in our model, such as distance between pots and velocity of travel, are not found in our data. However, our data does contain sufficient information for calibrating our model so that the predicted outcomes from our model are as close as possible to observed outcomes in our data. Given that there is no real consensus on what constitutes best practice for model calibration (Dawkins, Srinivasan and Whalley 2001), the methods in which we employ generally follow those found in the literature. That is, we use information from fishery participants, parameter estimates from our data, and information gathered from previous studies to set the values for a subset of the model parameters. For the remaining "free" parameters, values are chosen to minimize the proportional distance between certain model predictions and their median counterparts in the data for the year 2004, the last season before rationalization (see Table 1 of the paper). The methods used to select certain parameter values are described below, followed by a description of the proportional distance minimization strategy employed for the remaining free parameters. All parameter values used in our model are reported in Table A1.

TABLE A1
Model Parameter Values

Parameter	**Description**	**Value**
D	Congestion-free asymptotic catch per pot (crab)	40
γ	Rate of accumulation of catch per pot	2.33
p^{f}	Fuel price ($)	1.94
Θ	Scale parameter fuel consumption	2.19×10^{-6}
β	Rate of steaming cost growth	2.61
θ	Scale parameter crab deterioration	1.05×10^{-7}
σ	Rate of crab deterioration	5.56
$\bar{\rho}$	Ex-vessel price ($/crab)	30.67

c^{N}	Pot seasonal rental rate ($)	29.53
c^{p}	Pot pulling/setting cost per pot ($)	8.86
c^{l}	Labor provision cost per day ($)	205.3
c^{t}	Traveling cost (two ways) per trip ($)	3,047
T^{t}	Traveling time to and from fishing grounds (days)	1.83
H	Hold capacity (crabs)	28,829
TAC	Total allowable catch (crab)	2.2×10^{6}
$\bar{v}$	Maximum velocity (knots)	12.5
r	Vessel seasonal rental rate ($)	37,500
λ^{d}	Rate of density congestion index growth	0.77
m^{d}	Density at which congestion index growth is largest (nm^2)	12.6
λ^{N}	Rate of N_{-i} congestion index growth	1.54×10^{-4}
m^{N}	N_{-i} at which congestion index growth is largest (# of pots)	47,900
τ^{s}	Pot pulling/setting time per pot (minutes)	4.74

Note: The parameters λ^{d}, m^{d}, λ^{N}, m^{N}, and τ^{s} were chosen to minimize the distance between model predictions and their median counterparts (Table 1 of the paper).

Crab per Pot Production Function

We use data on soak times and corresponding catch per pot from the 2004 CIF data to estimate the parameters δD and γ from the saturating function in equation [7] using nonlinear least squares (Table A2a). The point estimate of γ is used as a parameter of the model while the estimated δD is used as a calibration point for the free parameters described later on in this section. Note that since the catch per pot production function in our model does not account for harvester heterogeneity, day of the season, or environmental conditions such as temperature and wind, there is no need to control for such things in our estimation procedure. Thus, our point estimates can be seen as marginalizing over all uncontrolled exogenous features that affect the crab per pot production function for the 2004 season.

TABLE A2
Nonlinear Least Squares Estimation Results

Equation	Parameter	Estimate	Std. Err.	P-value	[95% Conf. Int.]
(a) *crab per pot production*	δD	25.30	2.21	0.000	[20.95, 29.65]
($N = 233$)	γ	2.33	0.81	0.004	[0.734, 3.928]
(b) *crab deterioration*	σ	5.56	0.11	0.000	[5.363, 5.791]
($N = 245$)					

Note: (a) crab per pot production parameters of equation [7]; and (b) crab deterioration parameters of equation [10], constraining $\theta = 21^{-\sigma}$.

Velocity Cost Function

Following Wilson (1999), which examines the fuel usage of a typical small fishing vessel as a function of velocity, we use a convex function in velocity to represent fuel consumption per nautical mile traveled in equation [13]. For calibration purposes, we use three observations (Table A3) of fuel consumption (gallons per nautical mile) obtained from a study on the fuel usage of the Alaska Fish and Game 110-foot steel research vessel (Woodford 2008)—which is the same as the median vessel length of the RKC fishery in 2004—and choose Θ and β to minimize the distance between the three given points and the estimated curve:

$$\min_{\Theta,\beta} x(\Theta,\beta)' x(\Theta,\beta), \tag{A2}$$

where $x(\Theta,\beta)' = \left[\Theta(204)^{\beta} - 2.2353,\ \Theta(228)^{\beta} - 3.3684,\ \Theta(276)^{\beta} - 5.2174\right]$. Finding a solution to problem [A2] gives us the final values of Θ and β reported in Table A1. We choose the fuel price ρ^{f} to be the average of the fuel prices across all ports for the month of October 2004.[8]

[8] Fuel data were obtained from the Fisheries Economics Data Program, conducted by the Pacific States Marine Fisheries Commission (see http://www.psmfc.org/efin).

TABLE A3

Calibration Data Points for the Velocity Cost Function

Velocity		**Fuel**	
knots	nm/day	gal/hour	gal/nm
8.5	204	19	2.2353
9.5	228	32	3.3684
11.5	276	60	5.2174

Note: Data points represent fuel consumption as a function of velocity for a 110-foot steel vessel (Woodford 2008).

Technological Constraints: Hold Capacity and Maximum Velocity

The maximum velocity of a fishing vessel and its holding capacity (in terms of crab) are not directly observable in our data. Fortunately, we are able to obtain the maximum velocity and hold capacity for one specific vessel named the *Northwestern*, which participated in the RKC fishery in 2004.[9] At the time of its inauguration, the *Northwestern* was 108 feet in length, had a maximum velocity of approximately 12.5 knots, and could carry approximately 85 tons of live crab in circulating seawater, which, assuming the average crab weighs six-and-a-half pounds, is equal to 28,829 crab. We use these values for $\bar{v}$ and H, respectively, for our model calibration.

Fixed Costs and Pot Pulling Costs

We consider the fixed cost c^N to be the rental value for a single pot. We assume that fishermen rent pots for a season of three months[10] so that the seasonal rental rate for a pot is just one-fourth

[9] The *Northwestern* is an Alaskan crab, Pacific cod, and salmon tendering fishing vessel that became well recognized due to its starring role in the Discovery Channel's *The Deadliest Catch*, which follows skippers and their crew throughout an entire crab season. For more information on the *Northwestern*, see http://fvnorthwestern.com.

[10] The annual snow crab fishery has historically opened around January 15. Since many vessels fish in both fisheries, the season length of the RKC fishery is effectively truncated to three months.

of the annual rental rate.[11] Using an annual discount rate of 10% and the price of a single pot reported in Briand et al. (2004), we obtain the seasonal rental rate for a pot c^N reported in Table A1.[12] Similarly, the seasonal fixed cost r for entering a vessel in the fishery is the seasonal rental rate of the fishing vessel, where we assume that fishermen rent a vessel for a season of three months. Assuming that an average sized crabbing boat sold for $1.5 million in 2004 and a discount rate of 10%, the seasonal rental rate for a vessel is $37,500. The per pot pulling cost c^p is just the cost of bait used to put in the pot, the value of which is also taken from Briand et al. (2004) and converted into 2004 dollars.

Crab Deterioration Parameters

To account for crab deterioration over the course of a trip, we let the proportion of crab that is alive at delivery be a function of the amount of time spent at sea in equation (10). We use fish ticket data on live pounds delivered, pounds of dead crab, and days at sea for the year 2004 to estimate the parameters σ and θ using nonlinear least squares (Table A2b; Figure A2). Obtaining estimates of σ and θ is complicated by the fact that harvesters typically return to shore before crab deterioration has become rampant so that we are only able to reliably identify the initial portion of the deterioration curve. Discussions with crab harvesters suggest that if a crab dies while in the holding tank, it emits a poison that can quickly wipe out the entire catch. Since we do not typically observe trip lengths long enough for this phenomenon to occur, we choose a trip length—equal to one week longer than the longest observed days at sea in 2004 (14 days)—after

---

[11] Alternatively, if fishermen own their pots, then the seasonal rental rate is just the seasonal opportunity cost of foregone rental income from renting pots to other fishermen for the season.
[12] Specifically, Briand et al. (2004) report the 1997 price of a pot to be $1000. Converting this into 2004 dollars ($1181.55) and assuming that the value of a pot in 2004 has not changed since 1997, the seasonal rental rate satisfies $1181.55 = 4 \times c^N/disc$, where *disc* is the annual discount rate, which we assume to be 10%.

which all crab in the holding tank have died.[13] Thus, we constrain the parameter θ such that $\theta = 21^{-\sigma}$, giving us the final parameter values in Table A1.

Travel Costs

We assume that the cost of traveling back to shore from the fishing grounds is exogenous and constant throughout the season. This is equivalent to assuming that the fishing grounds for all fishery participants are all the same distance away from the port and all vessels travel to and from shore at the same speed. In order to place a legitimate value on the fixed cost of travel, we use the distance between the centroid of the most popular fishing are in 2004 and Dutch Harbor port.[14] Using this distance (220 nm), the velocity cost function described in Section III, and the assumption that all vessels travel at a constant speed of 10 knots when traveling to shore, we calculate the cost c^t and time T^t of travel between the fishing grounds and shore, whose values are reported in Table A1.

TAC and Labor Costs

The TAC for a given season is measured in pounds of crab. Assuming that the average crab is six-and-a-half pounds, we convert the 2004 TAC (1.43 million pounds) into crab to obtain the TAC reported in Table A1. The daily cost of labor provision c^l is obtained from the 2004 EDR data. We use information on the annual expenditure on food and provisions for crew, as well as the annual days at sea, to obtain the daily cost of labor provisions reported in Table A1.

---

[13] In fact, the lowest proportion of live crab observed in 2004 is 0.917 and the values of the first and fifth percentiles are 0.929 and 0.946 respectively. Note that time spent in the delivery line at the processor is included in the variable days at sea.

[14] The area in which a string of pots is dropped is recorded in the confidential skipper interviews, where the area refers to the 1° latitude by 0.5° longitude statistical reporting zones utilized by the Alaskan Department of Fish and Game. The most popular fishing zone is defined as the location that received the largest amount of pot retrievals during the 2004 season. Dutch Harbor is the most popular port to which vessels return to deliver crab for processing.

Calibrated Parameter Values

We lack external data to calibrate five parameter values $(\lambda^{d},\ m^{d},\ \lambda^{N},\ m^{N},\ \tau^{s})$, four relating to own and cross-pot congestion and the other representing the time to pull, set, and redeploy a pot. These free parameter values are chosen to minimize the proportional distance between selected outcomes predicted by the model and the median values of those outcomes found in our data for the 2004 season (Table 1 of the paper).[15] The selected outcomes and their data sources include soak time per pot (CIF data), pot lifts per day (CIF data), fishing days per trip (CIF data), number of registered pots (ADF&G Commercial Fisheries Division), crabs per pot (CIF data), and fuel consumption per crab caught (EDR data).[16]

Specifically, let Γ represent a vector of six sample medians, Ψ a vector of values for the five unknown parameters $\left[\lambda^{d},\ m^{d},\ \lambda^{N},\ m^{N},\ \tau^{s}\right]'$, and $\Lambda^{*}(\Psi)$ the SNE model prediction counterparts of Γ obtained using the parameter values contained in Ψ. Then Ψ is chosen to minimize the proportional distance between $\Lambda^{*}(\Psi)$ and Γ:

$$\min_{\Gamma}\ \left[\operatorname{diag}(\Gamma)^{-1/2}\left(\Lambda^{*}(\Psi)-\Gamma\right)\right]'\left[\operatorname{diag}(\Gamma)^{-1/2}\left(\Lambda^{*}(\Psi)-\Gamma\right)\right], \qquad \text{[A3]}$$

where $\operatorname{diag}(\Gamma)$ refers to a diagonal matrix with the elements of Γ along the diagonal. The parameter values in Γ that minimize the distance in [A3] are reported in Table A1 while the final model predictions $\Lambda^{*}(\Psi)$ are reported in column (4) of Table 1 of the paper.

---

[15] In order to remain consistent with the parameter values chosen for the velocity cost function, maximum velocity, and hold capacity, we use median values for vessels with length between 100 and 115 feet.

[16] Fuel consumption data in the EDR was deemed to be "measured with error" by the data audit described in Section I of this appendix, and may not be consistently measured over years. We justify our use of this data by pointing out that we are only using the median value from 2004 as a "ballpark" measure for calibration purposes and not to infer actual changes in fuel consumption in the RKC fishery. To ensure the latter inference is not made, we refrain from including fuel consumption per crab caught as part of our model validation exercise in Table 1.

IV. MEDIAN REGRESSIONS OF INPUT USE

While the change in the intensive use of inputs in Figure 3 is stark, there are confounding factors unrelated to ITQ introduction, such as weather conditions and output prices, which could be important in explaining the changes in input usage. To control for these factors, we estimate a median regression of the log of soak time and pot lifts per fishing day on average temperature and wind speed, ex-vessel prices, and vessel length, including fixed effects for different sizes of pots and for different seasons.[17] Using the estimated seasonal fixed effects, we compute the predicted percentage difference in median pot lifts per fishing day and soak time relative to 2004, along with their corresponding cluster robust 95% confidence intervals (Figures A3 and A4).[18] The results support the general findings from the box-and-whisker plots in Figure 3 while the upward trend in soak time prior to rationalization could be from the increase in pot limits in 2003 and 2004.

V. CONTINUOUS TREATMENTS OF THE CONSOLIDATION EFFECTS

To further examine the behavioral effects from consolidation, we consider treatments C and D from our hypothetical experiment (Figure 4) to be continuous along the interval between 78 and 232 vessels (Figures A5 and A6). Many intricate changes in harvesting behavior occur as vessels are successively eliminated from either fishery. First, a discrete shift in fishing practices in the IQ fishery marks the number of vessels at which the fleet makes the transition from one to two trips (Figure A6). This transition occurs before hold capacity is binding as IQ vessels reduce

---

[17] An attempt was made to control for fuel price, pot limits, and TAC, but they were ultimately dropped due to collinearity problems. The trend in all three variables is to increase over seasons with little to no variability within a season, leaving very little independent variation (with the inclusion of seasonal fixed effects) to identify their effect on input usage.
[18] Cluster robust confidence intervals were obtained from 500 pair-wise bootstraps, where clusters are defined at the trip level.

crab deterioration by spreading their seasonal harvest over two shorter trips. In contrast, the transition from one to two trips is not witnessed in the LE fishery (Figure A5) since, for the range of fleet sizes considered here, intensive derby behavior closes the season before the binding hold capacity constraint is reached. LE harvesters thus fail to make the transition to two trips until a much smaller number of vessels than in the IQ case–even though they would collectively be better off from reducing the amount of crab deterioration that occurs from longer trips. In addition, the trend in behavioral changes by LE harvesters is not affected when the transition to a second trip is made (not pictured), whereas IQ harvesters display a large reduction in the spatial and temporal intensity of their fishing practices after making the transition to two trips.

Second, the elimination of vessels from the fishery does not necessarily have a monotonic effect on the incentives to intensify input use with consolidation. This is seen by a *reduction* in spatial and temporal intensity as vessels are initially eliminated from the LE fishery (Figure A5), indicating that there is a competing mechanism—which we call a congestion effect—that operates alongside the consolidation effect as fleet size becomes smaller. As vessels exit the fishery, the number of pots in the fishery decreases, reducing cross-pot congestion and improving catch per unit effort for the remaining vessels. Improved catch per unit effort, *ceteris paribus*, allows fishermen to pursue a more relaxed pace of fishing since crab deterioration is no longer as much of a threat as before, resulting in reduced temporal and spatial fishing intensity.[19] The initial domination of the congestion effect indicates initial overcapacity in the LE fishery,

---

[19] Simulations in which vessels are successively eliminated from the fishery while the TAC is adjusted so that seasonal catch per vessel remains constant confirm the role of the congestion effect. These simulations mimic the qualitative reduction in intensity we've noted. However, once the fleet reaches a size in which cross-pot congestion is no longer elastic to further downsizing, eliminating vessels while keeping seasonal catch constant no longer affects harvester behavior.

placing fishermen on a relatively steep portion of the cross-pot inverse congestion curve. Productivity improvements from reduced congestion are initially so large in the LE fishery that the season length declines even as fleet size shrinks and the average scale of operations goes up. As downsizing continues, however, the marginal effect on cross-pot congestion shrinks in importance as the inverse congestion index approaches one, causing consolidation of the TAC on fewer vessels to become the dominant driver of behavior.

The IQ fishery reveals a subtly different picture in that the initial nonmonotonic effects of consolidation of TAC on fishing intensity witnessed in the LE simulations fail to materialize (Figure A6). Instead, the consolidation scale effect dominates throughout the entire range of the experiment. Congestion improves minimally in the IQ fishery with smaller η because the index is already near one in the IQ_{232} fishery due to much lower numbers of pots per vessel than under limited entry (Table 2).

Lastly, velocity of travel remains binding at $\bar{v}$ for all η in the LE fishery, and in fact, harvesters would travel faster as the number of vessels in the fishery decreases as indicated by the positive shadow value of velocity in Figure A5.[20] The binding maximum velocity forces harvesters to substitute imperfectly towards other inputs in order to increase their temporal input usage as consolidation intensifies, and it is this imperfect substitution that prevents LE fishermen from competing away all of the rents.

---

[20] The shadow value of velocity is defined here as an individual harvester's maximum willingness to pay for an "infinitesimally" small increase in their own maximum velocity, holding the actions of all other players at their SNE values.

References

Abbott, J. K., B Garber-Yonts and J. E. Wilen. 2010. "Employment and Remuneration Effects of IFQs in the Bering Sea/Aleutian Islands Crab Fisheries." *Marine Resource Economics* 25: 333-354.

Briand, G, T Heckelei, S C Matulich and R C Mittelhammer. 2004. "Managing fishing power: the case of Alaska red king crab (Paralithodes camtschaticus)." *Canadian Journal of Fisheries and Aquatic Sciences* 61: 43-53.

Dawkins, C., T.N. Srinivasan and J. Whalley. 2001. "Calibration." *Handbook of econometrics* 5: 3653-3703.

Grossmann, IE. 2002. "Review of nonlinear mixed-integer and disjunctive programming techniques." *Optimization and Engineering* 3: 227-252.

Judd, K. L. 1998. *Numerical Methods in Economics*. Cambridge, MA: The MIT press.

Lagarias, J.C., J.A. Reeds, M.H. Wright and P.E. Wright. 1998. "Convergence properties of the Nelder-Mead simplex method in low dimensions." *Siam journal of optimization* 9: 112-147.

Schelling, T. C. 1960. *The Strategy of Conflict*. Oxford: Oxford University Press.

Wilson, J K. 1999. "Fuel and financial savings for operators of small fishing vessels." *FAO Fisheries Technical Paper 383*.

Woodford, J. 2008. *Medeia Cuts Fuel Consumption 30 Percent Saves Thousands*. Available at http://www.adfg.alaska.gov/index.cfm?adfg=wildlifenews.view_article&articles_id=413 (accessed December 15, 2010).