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Strategic substitutes or complements? The game of where to fish

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Abstract

The ‘‘global game with strategic substitutes and complements’’ of Karp et al. (2007) is used to model the decision of where to fish. A complete information game is assumed, but the model is generalized to S > 1 sites. In this game, a fisherman's payoff depends on fish density in each site and the actions of other fishermen which can lead to congestion or agglomeration effects. Stable and unstable equilibria are characterized, as well as notions of equilibrium dominance. The model is applied to the Alaskan flatfish fishery by specifying a strategic interaction function (response to congestion) that is a non-linear function of the degree of congestion present in a given site. Results suggest that the interaction function may be non-monotonic in congestion.

1. Introduction

Understanding congestion externalities is important in many settings but is particularly relevant to natural resource economics. For example, Timmins and Murdock (2007) consider valuation of recreational sites while taking into account the effects of congestion on an individual's preferences over those sites. In the commercial fishing industry, vessels may respond to congestion in their decision of ‘‘where to fish’’. In other words, vessel captains behave strategically, and their location decisions are influenced by their interaction with other participants in the fishery. Vessels may agglomerate to increase safety as nearby vessels respond more quickly to distress signals (safety in numbers), while severe congestion may decrease safety as fishing gear become tangled. In the former scenario, the payoff to fishing a site increases with the number of vessels selecting the same site (strategic complements), while in the latter the payoff decreases with the number of vessels (strategic substitutes). The existence of both of these strategic responses (complements or substitutes) implies a strategic interaction function that is non-monotonic in congestion. The purpose of this paper is to specify a complete information game with strategic substitutes and complements (Karp et al., 2007), to characterize the equilibria that may exist, and to use vessel location data from the Bering Sea and Aleutian Island (BSAI) flatfish fishery to estimate a flexible interaction function within a random utility model framework (Bayer and Timmins, 2007; Timmins and Murdock, 2007). Results suggest that a nonmonotonic interaction function exists in the fishery.

The departure point for models of strategic complements or substitutes is the binary-action game of complete information (Bulow et al., 1985). If payoffs are monotonically increasing in congestion (strategic complements), then a unique equilibrium generally exists, while if payoffs are monotonically decreasing in congestion (strategic substitutes), then multiple equilibria may exist. Complete information holds when players possess full knowledge of some market signal, and players generally take the action when the market signal is strong. Karp et al. (2007) extend the binary-action model in interesting ways. First, they allow for an interaction function that is quasi-concave (non-monotonic) in congestion. That is, a player's payoff and interaction function are first increasing then decreasing as more players choose the crowd-inducing action.[1] Also, theirs is a global game in which each player receives a noisy realization of the market fundamental (market signals are heterogeneous across players). They find that when the noise is small and the congestion effect is weak, there exists a pure strategy equilibrium that is monotone in the market signal. That is, as the market signal improves, agents are more likely to take the action. However, if the congestion effect is strong, strategies are non-monotonic in the market signal. That is, a better signal may lead to the expectation of greater crowding, causing agents to take the action with lower probability.

In the context of fishing, we extend the Karp et al. (2007) model to the case where agents select one of *many* potential actions (multiple locations where vessels may fish) and where each action has a different market signal.[2] In commercial fisheries the market signal is the density of fish or expected catch in each location. However, complete information of the market signal is assumed. (Although this is a strong assumption, it may be reasonable in

[1] Karp et al. discuss the binary decision to ‘‘go to a bar’’ or ‘‘stay at home’’, where players have incentives to go to the bar if it has a good crowd (complements) but is not too crowded (substitutes) and where the market signal is the additively separable quality of the bar. Non-monotonicity of inter action only exists in the ‘‘go to the bar’’ (crowd-inducing) state.

[2] This is analogous to ‘‘multiple bars’’ in the world of Karp et al. (2007).

this case since all commercial fishing vessels are equipped with devices to detect fish and other vessels.) Therefore, the model is neither a generalization nor a special case of the Karp et al. (2007) model, but the notions of equilibria are similar. Existence of local equilibria is discussed, and equilibria are characterized (e.g., stable vs. unstable) as are notions of equilibrium dominance. Consequently, the assumption of quasi-concavity of the interaction function of Karp et al. (2007) can be relaxed and equilibria are characterized when the interaction function is more generally non-monotonic. Bayer and Timmins (2005) discuss existence of multiple equilibria when the interaction function is non-monotonic in congestion. They develop a sorting model of location choice, but their focus is existence of unique equilibria when the interaction function is monotonic in congestion (in fact, linear). The game presented here is effectively a sorting model of location choice, but the focus is actual characterization of the equilibria in the non-monotonic case.

This model also serves as an intellectual framework for estimation of a random utility model with an interaction function that is non-monotonic in congestion. Bayer and Timmins (2007) develop a random utility model of site choice in the style of Berry et al. (1995) that is linear (positive or negative) in site congestion. In the present paper, their procedure is generalized empirically, allowing utility to be a non-monotonic function of congestion (i.e., the interaction function is non-monotonic).[3] The non-monotonic interaction function and other model parameters are estimated for a panel of BSAI flatfish vessels. Results indicate that vessels may have a non-monotonic response to congestion, and that the general shape of the function is a third-order polynomial.

The paper is organized as follows. The next section develops a complete information game with strategic substitutes and complements and provides a discussion of stable and unstable equilibria, interior, semi-interior and corner equilibria, and notions of equilibrium dominance. Section 3 contains an empirical analysis of the BSAI flatfish fishery using the sorting equilibrium model of Bayer and Timmins (2005, 2007). Evidence that the interaction function in this fishery is non-monotonic in congestion is provided. Section 4 summarizes and concludes.

2. A Complete Information Game with Strategic Substitutes and Complements

The objective is to introduce the issue of how and why agglomeration and congestion effects can be present in commercial fisheries and to serve as an intellectual framework for the empirical analyses that follow. Our basic set-up follows Karp et al. (2007) with the restriction of complete information but generalized for several actions. An individual is considering which of S actions to take, $a \in \{1, \ldots, S\}$.We couch our discussion in terms of a visit to a fishing site $s = 1, \ldots, S$ and associate the action $a = s$ with ‘‘visiting site s’’. We assume, without loss of generality, that ‘‘not fishing’’ (staying in port) is not an option.[4] The individual is small and be-haves non-strategically, and the mass of individuals is 1. The utility that each individual receives from choosing ‘‘visit site s’’ depends on two factors: an underlying state (fish biomass, expected catch and other site-specific variables), denoted $\theta_s \in \Re_+$; and the fraction (share) of individuals who undertake the action, $\alpha_s \in [0, 1]$. The payoff function $U_s(\alpha_s)$ from choosing ‘‘visit site s’’ satisfies:

Assumption 1. $U_s(\alpha_s) = \theta_s + f(\alpha_s)$, where $f : [0, 1] \to \Re$.

Assumption 2. f is a bounded, differentiable function on $[0, 1]$ with $f(0) = 0, f'(0) > 0$ and a well-defined inverse, $f^{-1} : \Re \to [0, 1]$.

Assumption 1 implies that payoff at location s increases with the underlying state (market signal). Assumption 2 ensures that the derivative of profits is well-defined. It also ensures that there are agglomeration effects (increasing profits) in any site that contains zero (or very few) vessels. This is not needed in what follows; it is there to ensure that any vacant site with $\theta_s \geq 0$ has positive probability of a visit.[5] Save for the potential non-monotonicity of the interaction function, these assumptions are consistent with those maintained in the sorting model of Bayer and Timmins (2005, p. 465), which form the basis of the empirical model in Section 3. Therefore, the theoretical model is well-suited to serve as an intellectual framework for the empirical analysis.

2.1 Characterization of Equilibria

Since the profit function is non-monotonic there may be multiple equilibria (Bayer and Timmins, 2007).[6] Let equilibria be described by the S-tuple $[\alpha_1^*, \ldots, \alpha_S^*]$, where $\sum_s \alpha_s^* = 1$. We now develop basic notions of equilibria and

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[3] Per (Bayer and Timmins (2005), p. 436), their estimation strategy ‘‘at no point requires a unique equilibrium for estimation purposes’’. Also, it is the particular form of their likelihood function that determines the final equilibrium among many (Bayer and Timmins, 2007, p. 359). Therefore, their strategy is well-suited to the purpose at hand.

[4] This assumption may be problematic if the goal is to inform conservation policy, where fishing zone closures may lead ‘‘not fishing’’ being optimal. The goal here is to develop notions of equilibria in this setting and not to inform policy.

[5] Ultimately, if a site is not visited, then it is viewed as not contained in the set of actions and is eliminated.

[6] A unique equilibrium exists when $f(0) \neq 0$ and f is monotonically decreasing.

stability. First, when an equilibrium exists at a point on a payoff function that is increasing in congestion, $U_S'(\alpha_S^*) > 0$, we say that in equilibrium the location exhibits an agglomeration effect, otherwise we say it exhibits a congestion effect. Following Karp et al. (2007), our notion of stability is based on a process of tâtonnement or grouping. When an individual deviates from the equilibrium action, the effect is negligible because the individual possess zero mass. However, groups of individuals can affect an equilibrium in the same sense that groups of buyers and sellers in a Walrasian auction effect equilibrium prices. Logically, groups will only deviate from equilibria into sites exhibiting agglomeration effects. However, individuals possess complete information (instrumentation to detect the location of fish and other vessels), so movers may realize that their former (equilibrium) site exhibited congestion effects which were relieved upon their moving, thus increasing utility for stayers. If the gain in utility for stayers exceeds the gain in utility for movers, then movers will return to the equilibrium site, so the equilibrium point is considered stable. The actions of the groups are not coordinated (despite the ‘‘grouping’’ concept), so our notion of stability can produce equilibria that are suboptimal (coordination failure). Indeed, the previous example implied that both movers and stayers were made better off by the deviation of movers, yet the movers had an incentive to return, garnering lower utility for each group. Additionally, since there exists the potential for multiple equilibria, the system may ‘‘get stuck’’ at a low-payoff equilibrium, even though there may exist stable equilibria where all players can be made better off. In what follows we assume that all locations are fished without loss of generality.

Definition 1. A Nash equilibrium is the S-tuple $[\alpha_1^*, \ldots, \alpha_S^*]$, where $\sum_s \alpha_s^* = 1, \alpha_s^* \in (0, 1)$, and $U_1(\alpha_1^*) = \cdots = U_S(\alpha_S^*)$.

Obviously a stable equilibrium satisfies Definition 1 and does not provide incentives for groups of individuals to deviate (congestion effects); an unstable equilibrium does (agglomeration effects). Equilibria in this setting are best understood by examining the relationships between pairs of locations. Therefore, Definition 1 implies that equilibria satisfy for each pair s, j:

$$\alpha_j^* = f^{-1}\left[\theta_s - \theta_j + f(\alpha_s^*)\right] = g_{js}(\alpha_s^*), \quad s, j = 1, \ldots, S.$$

Since f is not guaranteed to be a one-to-one mapping, f^{-1} is not a function per se. A sufficient condition for existence of an equilibrium is that the equation:

$$\alpha_s = h_{sk}(\alpha_s) = g_{sk}\left(1 - \alpha_s - \sum_{j \neq k, s} g_{js}(\alpha_s)\right)$$

be satisfied with $h_{sk} : [0, 1] \to A_{sk}$ with $k, s = 1, \ldots, S$, and A_{sk} a non-empty, compact subset of [0, 1]. This is simply Kakutani's fixed point theorem. Unfortunately, the sufficient condition is unlikely to hold because Ask will not be compact in general, so existence in not guaranteed. By Brouwer's fixed point theorem a sufficient condition for existence of an equilibrium is that f be monotonic.[7] We seek conditions on h, g, f or f^{-1} that ensure an equilibrium without resorting to a monotonicity restriction.

To fix ideas en route to a more general result, consider the case where $\theta_s = \theta_j$ for all s, j. In this case an interior equilibrium is guaranteed to exist (trivially) at $\alpha_s^* = S^{-1}, s = 1, \ldots, S$, regardless of the nature of the interaction function, f. Therefore, there may be pieces of f around the point $\alpha_s^* = S^{-1}$ (or elsewhere) that admit an equilibrium when the differences between the θ_s are not too large. Regardless of the nature of f^{-1}, the function f is piecewise monotonic. Therefore, consider some monotonic piece of f on subdomain $[\underline{\alpha}, \bar{\alpha}] \subset [0, 1]$. Call this monotonic piece f_* with monotonic and one-to-one inverse, f_*^{-1}. The image of $[\underline{\alpha}, \bar{\alpha}]$ under f_* is the compact interval $[\underline{f}_{*\alpha}, \bar{f}_{*\alpha}]$ where $\underline{f}_{*\alpha} = \min\{f_*(\underline{\alpha}), f_*(\bar{\alpha})\}$ and $\bar{f}_{*\alpha} = \max\{f_*(\underline{\alpha}), f_*(\bar{\alpha})\}$. Now consider some compact interval $[\underline{a}, \bar{a}] \subseteq [\underline{\alpha}, \bar{\alpha}]$. Then the image of $[\underline{a}, \bar{a}]$ under f_* is the compact interval $[\underline{f}_{*a}, \bar{f}_{*a}] \subseteq [\underline{f}_{*\alpha}, \bar{f}_{*\alpha}]$.

Proposition 1. *If there exists some compact interval $[\underline{a}, \bar{a}] \subset [\underline{\alpha}, \bar{\alpha}]$ for which:*

$$\alpha_s = f_*^{-1}[\theta_k - \theta_s + f_*\{1 - \sum_{j \neq k} f_*^{-1}[\theta_s - \theta_j + f_*(\alpha_s)]\}] \in [\underline{a}, \bar{a}],$$

$$s = 1, \ldots, S,$$

with $\sum_s \alpha_s = 1$, then an equilibrium exists on $[\underline{a}, \bar{a}]$, with $\alpha_s^* \in [\underline{a}, \bar{a}]$, $s = 1, \ldots, S$.

Continuity and monotonicity on the subdomain $[\underline{\alpha}, \bar{\alpha}]$ ensure that the function on the RHS of the equation in Proposition 1is continuous, and the result follows from Brouwer's fixed point theorem. Since f may have several

[7] These are precisely the arguments of Bayer and Timmins (2005) who assume f is linear.

monotonic pieces there may be many compact subsets of the unit interval that satisfy Proposition 1. We now attempt to understand the nature of the interval, $[\underline{a}, \bar{a}]$ in terms of the model's parameters.

For Proposition 1 to hold, we see that the outer function $f_*^{-1}[\theta_k - \theta_s + f_*(\alpha_k)]$ (on the RHS of the equation in Proposition 1) must map into $[\underline{a}, \bar{a}] \subseteq [\underline{\alpha}, \bar{\alpha}]$ through the monotonic portion of f_*^{-1}. Therefore its domain must be the compact set $[\underline{f}_{*\alpha}, \bar{f}_{*\alpha}]$. Since the condition in Proposition 1 must hold for all locations, it must hold for the kth, so for the proposition to hold it must be true that $\alpha_k \in [\underline{a}, \bar{a}]$. Hence, the relevant subdomain of $f_*^{-1}[\theta_k - \theta_s + f_*(\alpha_k)]$ must be contained in the compact set $[\underline{f}_{*\alpha} + \theta_k - \theta_s, \bar{f}_{*\alpha} + \theta_k - \theta_s] \subseteq [\underline{f}_{*\alpha}, \bar{f}_{*\alpha}]$. This last condition must also hold more generally (for = 1, . . . , S). Let ranked θ_s be $\theta_{[S]} \geq \theta_{[S-1]} \geq \cdots \geq \theta_{[1]}$, and let $d = \theta_{[S]} - \theta_{[1]} \geq 0$. Therefore, we have the following result.

Proposition 2. *A sufficient condition for Proposition 1 to hold is that there exists some compact* $[\underline{f}_{*\alpha}, \bar{f}_{*\alpha}] \subset \Re$ *that satisfies* $[\underline{f}_{*\alpha} - d, \bar{f}_{*\alpha} + d] \subset [\underline{f}_{*\alpha}, \bar{f}_{*\alpha}]$.

Notice that f_*^{-1} will map $[\underline{f}_{*\alpha}, \bar{f}_{*\alpha}]$ into [a, ¯a], while the more general f^{-1} will map it into a subset of [0, 1] that contains $[\underline{a}, \bar{a}]$. This subset will not be compact in general, so a fixed point may not exist in general. By limiting attention to f_*^{-1}, the mapping is one-to-one and continuous. It is also important to note that, thus far, we have presumed that all the locations, s = 1, . . . , S are fished in equilibrium. The implication for Propositions 1 and 2 is that the locations are similar in their attributes θ_s and, hence, that $d \geq 0$ is small. Therefore, the set of interest, $[\underline{f}_{*\alpha} - d, \bar{f}_{*\alpha} + d]$, will be approximately equivalent to $[\underline{f}_{*\alpha}, \bar{f}_{*\alpha}]$ and, hence be contained in $[\underline{f}_{*\alpha}, \bar{f}_{*\alpha}]$. When $\theta_s = \theta_j$ for all s, j, then d = 0 and $[\underline{a}, \bar{a}]$ is some neighborhood around the point $\alpha_s^* = S^{-1}, s = 1, \ldots, S$. The larger is $d \geq 0$, the wider the interval $[\underline{f}_{*\alpha} - d, \bar{f}_{*\alpha} + d]$ and the wider the interval [f ∗α, ¯f ∗α] required for some portion of the interaction function f . The width of the interval $[\underline{f}_{*\alpha}, \bar{f}_{*\alpha}]$ is (in some sense) a proxy for the degree of monotonicity of f, for if f is monotonic for all α, then $[\underline{f}_{*\alpha}, \bar{f}_{*\alpha}]$ is the image of [0, 1] under f. Additionally, the sufficient condition in Proposition 2 is probably more general than is necessary, since we could have defined some subset $[\underline{a}, \bar{a}]_s$ for each location over which a fixed point might exist, but having a general $[\underline{a}, \bar{a}]$ simplifies the exposition.

2.2 Equilibrium Stability and Dominance

For completeness, this subsection is devoted to characterizing notions of stability and dominance in our particular model. In the previous discussion we assumed that all locations are fished. In what follows we relax this assumption and consider situations where locations may be dominated by sets of other locations.

Definition 2 (*Strong Stability*). A *strongly stable* interior equilibrium is one with congestion effects at each site. That is, $f'(\alpha_s^*) \leq 0$ for all $s = 1, \ldots, S$ in equilibrium.

The salient feature of a strongly stable equilibrium is that global congestion effects create disincentives to switch sites in equilibrium.

Definition 3 (*Instability*). An *unstable* interior equilibrium is one for which there exists some s with agglomerations effects, $f'(\alpha_s^*) > 0$, and $U_s(\alpha_s^* + \varepsilon) > U_j(\alpha_j^* - \varepsilon)$ for all $j \neq s$ and for ε small and positive.

The idea of instability here is that there is an agglomeration effect in some location s, creating incentives to move out of $j \neq s$ into s. However, the movers $(+\varepsilon)$ are made better off, and stayers $(\alpha_j^* - \varepsilon)$ are made worse off, so everyone has an incentive to move into s. Sites $j \neq s$ can exhibit either agglomeration or congestion effects in equilibrium. If all $j \neq s$ exhibit congestion effects, then for the equilibrium to be unstable the benefits of leaving, $U_s(\alpha_s^* + \varepsilon)$, must outweigh the benefits of staying when others leave, $U_j(\alpha_j^* - \varepsilon)$. A sufficient condition for an equilibrium to be unstable is that at least two sites exhibit agglomeration effects. So far we have assumed an interior solution, we now discuss corner solutions and notions of locational dominance.

Definition 4 (*Corner Equilibrium*). A corner equilibrium is the S-tuple $[\alpha_1^*, \ldots, \alpha_S^*]$, where $\alpha_s^* = 1$ for some s, $\sum_s \alpha_s^* = 1$, and $U_s(1) > \theta_j$ for all $j \neq s$.

At a corner equilibrium, payoffs in each site are not necessarily equal. The corner equilibrium gives rise to notions of locational dominance. Let Let $\bar{f} = \max_\alpha f(\alpha)$ and $\underline{f} = \min_\alpha f(\alpha)$

Definition 5 (*Strong Dominance*). Site s *strongly dominates* site j if $\theta_s - \theta_j > \bar{f} - \underline{f}$.

If any site j is strongly dominated by any site s, then site j will not be fished in equilibrium. That is, $\alpha_j^* = 0$. The result follows from the fact that any vessel in site j will always have a higher payoff if it switches to site s.

Definition 6 (*Weak Dominance*). Site s *weakly dominates* site j if $\theta_s - \theta_j > f(\alpha) - f(1 - \alpha)$ for all $\alpha \in [0, 1]$.

If site s strongly dominates site j, then it weakly dominates j. This result follows from the fact that $\bar{f} - \underline{f} \geq f(\alpha) - f(1-\alpha)$ on [0, 1].

Definition 7 (*Weak Stability*). A *weakly stable* interior equilibrium has for each $s = 1, \ldots, S$ with $U_s'(\alpha_s^*) > 0$, some $j \neq s$ such that $U_j(\alpha_j^* - \varepsilon) > U_s(\alpha_s^* + \varepsilon)$ for ε small and positive.

At a weakly stable interior equilibrium there appears to be an incentive to deviate into s, because $U_s'(\alpha_s^*) > 0$. However, once vessels move into s from any $j \neq s$, the stayers gain higher payoff than the movers, so there is an incentive for movers to return to $j \neq s$. Weak stability is a fairly strong condition, because no matter where vessels leave, staying vessels are always better off regardless of where they are. Weak stability means there are incentives to deviate but stronger incentives to return after deviation.

Definition 8 (*Semi-interior Equilibrium*). Let $S^* \subset \{1, \ldots, S\}$ such that $U_s(\alpha_s^*) = U_j(\alpha_j^*)$ and $\alpha_s^* \in (0, 1)$ for all $j, s \in S^*$ and $\sum_s \alpha^*_{s \in S^*} = 1$, then the S-tuple $[\alpha_1^*, \ldots, \alpha_S^*]$ is a semi-interior equilibrium.

Essentially there may exist equilibria where some sites are not visited, $s \notin S^*$, and those sites that are visited, $s \in S^*$, possess an interior solution. A semi-interior solution will be stable or unstable based on Definitions 1, 2 and 7, but for S^* and not {1, . . . , S}. Definition 8 leads to a third concept of dominance.

Definition 9 (*Equilibrium Dominance*). A site j is dominated by a stable semi-interior equilibrium if the equilibrium exists and $j \notin S^*$.

The point here is that a site may neither be strongly nor weakly dominated by any or all other sites individually, but it may still be dominated by a particular stable equilibrium point. In other words, a site that is not strongly or weakly dominated may remain unvisited in equilibrium. This is a different form of dominance than those previously defined, so it is difficult to make direct comparisons.

3. Empirics

In the fishery economics literature the theory of congestion externalities was initially proposed by Brown (1974), however to the best of our knowledge, empirical work has not been conducted on fisheries data. There have been a few empirical papers that investigate congestion in the recreational demand literature (McConnell, 1977; Timmins and Murdock, 2007). Empirical modeling of preferences in the presence of congestion externalities is challenging because congestion, α, is endogenously determined by an agent's selection of where to locate which is, in turn, a function of congestion. While this endogeneity is certainly present in the equilibrium model of Section 2, the assumption of a continuum of representative agents with zero mass greatly simplifies that analysis, and of course parameter identification and estimation is not an issue. However, the endogeneity issue becomes the central challenge for any empirical implementation of this equilibrium model, particularly since agents are (in reality) discrete, have positive mass (in the distribution of agents), and have heterogeneous tastes and technology. Of course most empirical implementations of equilibrium models of strategic behavior would suffer from these same issues, so we are not alone. That being said, there remains a clear and strong connection between the concepts of the last section and those of the empirics that follow.

Our empirical approach follows that of Berry et al. (1995), which, unfortunately, does not address the issue of multiple equilibria. More recently Tamer (2003), Aradillas-Lopez and Tammer (2008) and Ciliberto and Tamer (2009) consider empirical investigations of entry models with multiple equilibria. Tamer (2003) considers identification and estimation of a static, bivariate entry model with multiple equilibria. Estimation follows from restrictions on the probabilities of non-unique outcomes. Aradillas-Lopez and Tammer (2008) consider similar models with rational behavior (replacing Nash behavior) and provide ''constructive identification results that lead naturally to consistent estimators''. Ciliberto and Tamer (2009) consider partial identification of parameters in an empiricalmodel of airline entry. Their econometric framework is a multiplayer generalization of Tamer (2003); it exploits the Tamer's restrictions on the probabilities of non-unique outcomes to bound choice probabilities which partially identifies the models parameters.[8]

Consider a vessel (fisherman) deciding among S sites, each having payoffs R_s and costs of access equal to C_s. Based on the game-theoretic model of Section 2, suppose that the agent's payoff in site s is impacted by share of the fleet at site s via the interaction function $f(\alpha_s)$. Following a standard random utility model, the vessel chooses site s over all other j sites if:

$$\beta_1 R_s + \beta_2 C_s + f(\alpha_s) + \varepsilon_s > \beta_1 R_j + \beta_2 C_j + f(\alpha_j) + \varepsilon_j \quad \forall j,\ s \in S. \tag{1}$$

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[8] Ultimately, our purpose is to identify point estimates of parameters in a multiplayer, multiple-choice Nash model, so none of these approaches are wellsuited to the goals of this research. In future research partially identified models will be explored.

The site-specific error terms are observed by vessels but unobserved by the econometrician. If site s is selected, it may be due to high expected revenues, low costs, or a high value of ε_{s}. We note here that the observables and unobservable in Eq. (1) are not vessel-specific. While this is in keeping with the theoretical model of Section 2, ultimately we incorporate vessel-specific information into the empirical model and, hence, deviate from the theory.[9] If other fishermen are aware of this unobservable desirable attribute of site s, then congestion is also likely to be high at the site. Consequently, there is an unavoidable correlation between the share of the fleet visiting the site, α_{s}, and unobserved site-specific attributes, ε_{s}. This makes identification of f challenging. Bayer and Timmins (2007) propose a two-stage instrumental variable approach to identify a monotonic f. That is, they let $f(\alpha_s) = \beta_3\alpha_s$, say, in Eq. (1) and consistently estimate β_1, β_2 and β_3. The sign of β_3 determines if player's strategies are purely complements or substitutes. As discussed in Timmins and Murdock (2007), the model is similar to a static, simultaneous-move Nash bargaining model where agents make decisions conditional on their expectations regarding competing agents. Their model is particularly relevant in our case, since the underlying equilibrium of the spatial distribution of economic activity allows the parameters in Eq. (1) to be estimated. However, we moderately extend the empirical model of Bayer and Timmins (2007) by assuming that a sorting equilibrium across sites occurs each day throughout the season.[10] Thus, we incorporate a time dimension in our estimation methodology, and the payoff vessel i derives from visiting site s at time t is,

$$V_{ist} = \delta_{st} + G'_{ist}\gamma + \varepsilon_{ist} \qquad i = 1,\ldots,N;\ s = 1,\ldots,S;\ t = 1,\ldots,T \tag{2}$$

where δ_{st} is given by the partial linear model

$$\delta_{st} = X'_{st}\beta + f(\alpha_{st}) + \eta_{st}. \tag{3}$$

The matrix X_{st} contains site-specific data (e.g., revenues, bycatch, etc.), G_{ist} contains information that varies across vessels (distance traveled to arrive at the location), δ_{st} (an unobservable constant) represents the baseline payoff from visiting site s before accounting for vessel-specific information, and η_{st} is the unobservable portion of site-specific payoff. Eq. (3) corresponds to the site-specific payoff function used to characterize equilibria in Assumption 1. The $X'_{st}\beta + \eta_{st}$ portion of Eq. (3) is the timevarying equivalent of θ_{s}, and we are effectively evaluating vessel interaction over daily equilibria in Assumption 1. This is the sense in which our theoretical model is tied to the empirical analysis. Essentially, we estimate θ_{s} and f using the partial linear model of Eq. (3). We may then examine the functional form of f to understand how strategic responses to congestion may change with the level of congestion.

Each vessel maximizes its utility over S spatial alternatives, given their expectations on the actions of the others which influences α_{st}. Assuming that ε_{ist} is distributed i.i.d. extreme value, the probability that the ith vessel selects site s in period t is,

$$p_{ist}(\delta,\gamma) = \frac{\exp\{\delta_{st} + G'_{ist}\gamma\}}{\sum_{j=1}^{S}\exp\{\delta_{jt} + G'_{ijt}\gamma\}}. \tag{4}$$

Then the predicted share of vessels visiting sites in period t is,

$$\hat{\alpha}_{st}(\delta_t,\gamma) = \frac{1}{N}\sum_{i=1}^{N} p_{ist}(\delta_t,\gamma). \tag{5}$$

The maximum likelihood estimates $\hat{\gamma}$ and $\hat{\delta}$ are obtained from the optimization,

$$\max_{\delta,\gamma} L(\delta,\gamma \mid G_{ist}) = \prod_{i=1}^{N}\prod_{s=1}^{S}\prod_{t=1}^{T}\left(\frac{\exp\{\delta_{st} + G'_{ist}\gamma\}}{\sum_{j=1}^{S}\exp\{\delta_{jt} + G'_{ijt}\gamma\}}\right)^{Y_{ist}} \tag{6}$$

$$\text{s.t. } \alpha^{*}_{st} = \frac{1}{N}\sum_{i=1}^{N} p_{ist}(\delta_{st},\gamma) \quad \forall s,t, \tag{7}$$

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[9] In this setting it may be possible to solve a global game in the style of Karp et al. (2007) where agents receive an individual market signal, thereby allowing for the incorporation of agent-specific observables and unobservables. This is currently being considered by the authors.

[10] In the Alaskan Yellowfin Fishery during the years 2000–2004, fishing occurs on 957 unique days across 71 sites.

where α^*_{st} are the observed equilibrium share of vessels in site s in period t, and y_{ist} equals 1 if vessel i selects site s in period t, and zero otherwise.[11] For any estimated value of γ, a vector of site-and time-specific baseline payoff estimates (δ_{st}) is recovered that preserves the observed sorting equilibrium (i.e., preserves α^*_{st} in Eq. (7)). Ideally, one could estimate a full information maximum likelihood model by plugging Eq. (3) into (2) and estimating the two functions jointly. However this is intractable given that there are 5313 δ_{st}s that must be estimated and that they satisfy the equality constraint in Eq. (7).[12] Berry (1994) proposes a contraction mapping that simplifies the search over the parameter space and guarantees that the equilibrium shares satisfy Eq. (7). For each iteration, ℓ, over the parameter space of the likelihood function, define contraction mapping

$$\hat{\delta}_{st}^{(\ell+1)} = \hat{\delta}_{st}^{(\ell)} - \ln\left[\alpha^*_{st} - \hat{\alpha}_{st}(\hat{\delta}_{st}^{(\ell)}, \hat{\gamma}^{(\ell)})\right]. \qquad (8)$$

The mapping ensures that site-specific constants move toward the observed sorting equilibrium for any value of $\hat{\gamma}$. The technique is amenable to problems having large numbers of constants.

Since we assume an extreme value distribution for the error in Eq. (2), we implicitly impose Independence from Irrelevant Alternatives (IIA).[13] We explored using Hausman–McFadden test of IIA, but these tests are motivated and conducted on the basis of well-formed priors for the grouping of choice alternatives. We have no a priori basis for forming groups of fishing locations. Admittedly, we could examine different ad hoc groupings of sites over each of the 71 spatial locations, employing a grid-search-type approach to the test. However, we have elected not to do this and note that many spatial choice papers fail to do so unless groupings of sites over types of site usage or geographic organization are self-evident.

The estimation algorithm proceeds in two-stages. In the first stage Eq. (6) is maximized subject to (7) with iterations based on (8). In the second stage, the $\hat{\delta}_{st}$ are treated as dependent variables in Eq. (3), and $f(\alpha_{st})$ is estimated. In what follows the first stage is always the same, however in the second stage a variety of estimation strategies are employed, based on different assumptions on the functional form of f and on the presence of endogeneity through α_{st}.

3.1 Data Description

Data for this analysis come from the Alaska Fisheries Science Center's Observer Program Database, which contains production information on vessels operating within the BSAI with 100% of all spatial production observed for vessels greater than 125 ft in length and with 30% coverage for vessels less than 125 ft. The data were collected during 2000–2004, using federal observers who are aboard each vessel while at sea and who record information on the GIS coordinates of each fishing haul (deployment of gear), the composition of the catch and other biological information relevant to fisheries management. Over this period there were 975 days when vessels fished. Because we do not perfectly observe the spatial behavior of vessels less than 125 in length, we focus the analysis on only those vessels with 100% spatial coverage.[14]

Using the GIS coordinates of each haul, spatial identifications are assigned that are consistent with the statistical reporting zones used by the Alaska Department of Fish and Game. Zones divide the BSAI into grids with each cell's dimension being 1/2 degree latitude by 1 degree longitude, of which there are 71 unique spatial sites within our data set. Distances are calculated using the centroids of each cell within the grid defining the spatial sites within the BSAI. Price data for the fishery are from the Commercial Fisheries Entry Commission (CFEC) fish ticket and Commercial Operator Annual Report (COAR) and represents the ex-vessel value of fish landed.

The focus is the yellowfin sole fishery operating in the BSAI, which is part of the larger head-and-gut fleet operating in the fishery. Targeting designations are based on National Marine Fisheries Service guidelines, which specify that a vessel is targeting yellowfin sole if more than 50% of its catch is flatfish (yellowfin sole, rock sole, flathead sole, rex sole, etc.) and if more than 70% of that 50% consists of yellowfin sole. In addition, our analysis focuses solely on catcher-processors in the BSAI and does not include the

[11] Given that our data are at the ''haul'' level (individual deployments of fishing gear) i is actually defined as the haul.

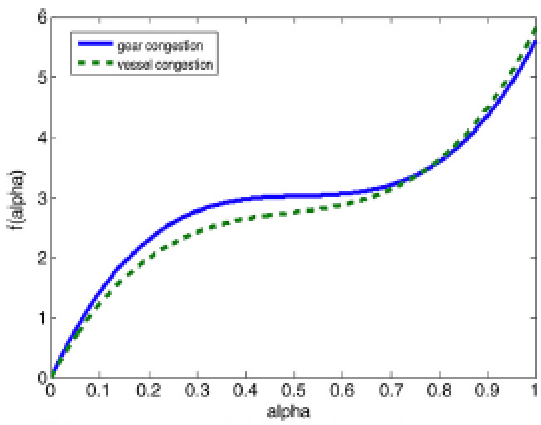
[12] To focus our analysis we only look at those sites in which fishing actually takes place on a given day. We do not use a spatially balanced panel in our estimation because there are many zero-effort sites on a given day in our data.

[13] We thank an anonymous referee for pointing this out to us.

[14] This may cause problems for estimating congestion equilibria, as smaller boats may be more capable of ''squeezing'' into already congested waters. Excluding them may understate crowding and overstate reactions to congestion.

Table 1
Descriptive statistics: yellowfin sole fishery 2000–2004 (expressed in 2004 dollars).

Yellowfin sole	Mean	Std. dev.	Min	Max
Cruise revenue	$55,387.39	$52,604.27	0	$252,238.15
Haul revenue	$643.67	$1,032.13	0	$18,198.56
Cruise length (hauls)	80.19	62.02	1	335
Cruise length (days)	21.00	16.61	< 1	79
Sites per cruise	8.16	4.93	1	32
Sites per day	1.74	0.76	1	5



Model 1 = Gear Congestion. Model 2 = Vessel Congestion.

Fig. 1. Third-order polynomial $f(\alpha)$, endogeneity ignored.

smaller catcher vessels operating in the fishery. Although this may seem limiting, the 43 Vessels in our data harvest over 80% of the annual yellowfin sole catch each year.

Table 1 has descriptive statistics for the fleet. On the average fishing cruise a vessel earns approximately $55,400 (expressed in 2004 $'s), conducts approximately 80 hauls spaced over 21 days, visits approximately eight uniquely different locations and visits slightly less than two sites a day. The fact that vessels often times conduct repeated hauls (gear deployments) in the same location on a given day will be accounted for in our empirical analysis as we differentiate between vessel and gear congestion/agglomeration.

3.2 Estimation

The traditional way to conceptualize congestion is as the number of decision makers competing in a location or market. However, in the commercial fishing industry ''gear interactions'' are particularly important to the concept of congestion. That is, the count of vessels in a location is important to congestion, but the frequency of deployment of fishing gear in a location may be an equally important congestion concept. In the empirics that follow we consider both vessel counts and gear deployments as measures of congestion. To investigate gear congestion we treat each haul (deployment of gear) as a unique observation and estimate shares based on the total level of gear effort in a given location. We refer to this gear congestion model as Model 1 in our discussion of the results. To investigate vessel congestion we only use the first haul conducted by each vessel on a given day and estimate shares based on the total number of vessels that deployed gear in a given location. We refer to this vessel congestion model as Model 2. We compare the results of the two congestion specifications.

In Eq. (4), $G_{ist} = DISTANCE_{ist}$, the distance traveled by vessel i on day t from its last spatial location to location s. This distance is a proxy for marginal costs (e.g., fuel, labor, opportunity cost), which are vessel specific.[15] Estimates of $\hat{\delta}_{st}$ and $\hat{\gamma}$ are recovered from Eqs. (4)–(8). The value of $\hat{\gamma}$ is −0.0280 for Model 1 and −0.0136 for Model 2, however only Model 1's coefficient is statistically significant. These results suggest that in general vessel payoffs are lower at more distant sites. The specification selected for Eq. (3) is,

$$\hat{\delta}_{st} = \beta_t + \beta_1 REV_{st} + \beta_2 STDV_{st} + \beta_3 BYCATCH_{st} + f(\alpha_{st}) + \eta_{st}, \quad (9)$$

where REV_{st} is site- and time-specific revenue (average fleet-wide catch over the last 30 days in each location in each day multiplied by the landed price), $STDV_{st}$ is the standard deviation of those revenues, and $BYCATCH_{st}$ is the expected

[15] DISTANCE is the only observable in the analysis that could be constructed to vary over vessels. This is due to limitations in the variability of the other observables once they were allocated to different spatial locations, given our predetermined definition of the spatial resolution.

bycatch (the incidental catch of non-target and non-marketable species also based on average fleet-wide catch over the last 30 days). The β_t parameters can be interpreted as a game-specific constants (estimated for each day) in the sorting equilibrium model because they correspond to the temporal resolution at which we measure congestion. What follow are several attempts to estimate $f(\alpha_{st})$ in Eq. (9).[16]

As a first pass, endogeneity is ignored, so $E[\eta_{st}|\alpha_{st}] = 0$ (this assumption will be relaxed in the next section), the interaction function is parameterized as the third order polynomial,

$$f(\alpha_{st}) = \lambda_1\alpha_{st} + \lambda_2\alpha_{st}^2 + \lambda_3\alpha_{st}^3, \qquad (10)$$

and Eq. (9) is estimated using OLS.[17] Parameter estimates for Models 1 and 2 are in the first two columns of Table 2 respectively, and the estimates of the interaction functions are depicted in Fig. 1.[18] Standard errors are not corrected for any potential temporal or spatial correlations, but again we are only trying to get a sense of the curvature of f. Based on our results for Models 1 and 2, the market signal $(\hat{\delta}_{st})$ is increasing in expected revenues (β_1), decreasing in the variability of those revenues (β_2), and increasing in the expected bycatch (β_3). These results are robust to our specification of congestion (compare Models 1 and 2), however the positive coefficient on bycatch seems odd since vessels tend to avoid bycatch at certain times during the fishing season, however in the final specification the coefficient on bycatch is insignificant for both models. Fig. 1 suggests that the interaction function is monotonic in gear and vessel shares (congestion) in Models 1 and 2 (respectively) when endogeneity is ignored across both specifications of congestion.

Based on the assumption that $E[\eta_{st}|\alpha_{st}] = 0$, Eq. (9) can also be semi-parametrically estimated using the partial-linear estimator of Robinson (1988). Given the assumption that $E[\eta_{st}|\alpha_{st}] = 0$ we have the following,[19]

$$\begin{aligned}\delta_{st} &- E[\delta_{st}|\alpha_{st}] \\ &= \beta_1[REV_{st} - E[REV_{st}|\alpha_{st}]] + \beta_2[STDV_{st} - E[STDV_{st}|\alpha_{st}]] \\ &\quad + \beta_3[BYCATCH_{st} - E[BYCATCH_{st}|\alpha_{st}]] + \eta_{st}. \qquad (11)\end{aligned}$$

The conditional expectations are non-parametrically estimated using an arbitrarily selected Gaussian kernel with optimal

Table 2
Preliminary estimates ignoring endogeneity of vessel shares.

	Parametric		Semi-parametric			
Parameter	Model 1	Model 2	Model 1	Model 1 Bandwidth	Model 2	Model 2 Bandwidth
γ	−0.0280** (0.0077)	−0.0136 (0.0114)	–	–	–	–
β_1	0.0005 (0.0005)	0.0004 (0.0002)	−0.0026 (0.0023)	0.0670	−0.0012 (0.0014)	0.0172
β_2	−0.0012** (0.0002)	−0.0003** (0.0001)	−0.0001 (0.0008)	0.0067	0.0007 (0.0005)	0.0012
β_3	0.0014** (0.0006)	0.0003 (0.0003)	0.0009 (0.0033)	0.0364	0.0057** (0.0021)	0.5065
λ_1	17.23** (0.0920)	14.81** (0.0671)	–	–	–	–
λ_2	−33.10** (0.3091)	−28.23** (0.2396)	–	–	–	–
λ_3	21.47** (0.2752)	19.33** (0.2327)	–	–	–	–

Standard errors are in parentheses.
** Indicates significance at the 95% level.

bandwidth selection using least-squares cross validation.[20] After estimation of Eq. (11), f (α) can be estimated semi-parametrically as

$$\begin{aligned}\hat{f}(\alpha_{st}) &= \hat{E}[\delta_{st}|\alpha_{st}] - \hat{\beta}_1\hat{E}[REV_{st}|\alpha_{st}] - \hat{\beta}_2\hat{E}[STDV_{st}|\alpha_{st}] \\ &\quad - \hat{\beta}_3\hat{E}[BYCATCH_{st}|\alpha_{st}]. \qquad (12)\end{aligned}$$

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[16] The specification could also include time-invariant location dummies, but we chose to exclude them.
[17] A 3rd-order polynomial was selected based on F -tests. F -tests for the final IV model are presented in the sequel.
[18] For brevity, we do not report the nearly one thousand game specific constants (βt) for any of our second stage results. These constants are available from the authors.
[19] We thank Andres Aradillas-Lopez for the suggestion to use Robinson (1988) semi-parametric estimator.
[20] The least-squares cross validation routine was coded in MATLAB using the constrained optimization routine with a lower bound of 0 and an unconstrained upper bound. Bandwidth was selected using the interior-point algorithm in MATLAB.

The idea is that, even though endogeneity is ignored, the semiparametric estimator of $f(\alpha)$ will provide a sense of how well the parametric polynomial of Eq. (10) fits the data. The results of the semi-parametric estimation are in the last four columns of Table 2. The first two are for Model 1 (gear) and last two for Model 2 (vessels). The coefficients are insignificant, but the plot of the interaction function in Fig. 2 for both Model 1 (left pane) and Model 2 (right pane) appears to confirm that the interaction function is close to a third-order polynomial. In fact, the shapes of the functions in Figs. 1 and 2 are surprisingly similar. The magnitudes are different, but the curvatures are close. In what follows, Eq. (9) is estimated under the assumption of endogenous shares, $E[\eta_{st}|\alpha_{st}] \neq 0,$ using both the parametric and semiparametric model specification for Models 1 and 2.

3.3 Instrumental Variables Estimation

As pointed out by Bayer and Timmins (2007), the share of agents selecting a site, α_{st}, is correlated with the error term, η_{st}. To circumvent this, they developed an instrumental variables approach for identifying congestion/agglomeration effects that leverages the exogenous data (information on the other sites not selected) in the model as well as the spatial and, in our case, temporal variation to obtain instruments that are correlated with share but are uncorrelated with the error term, η_{st}. [21] The logic behind using the set of instruments they propose is that the desire to fish in a given location is determined not only by the location-specific information, but also by the relative comparison of this information with the other potential locations one may fish. Therefore, information from other sites can be used as instruments for the share of fishermen that select a given site (Bayer and Timmins, 2007).

Introduction of non-linear $f(\alpha)$ presents no additional difficulties to this identification approach (Bayer and Timmins, 2007, footnote 18). Based on F -tests the appropriate specification for $f(\alpha_{st})$ in Eq. (10) is a cubic function for Model 1, and a quadratic for Model 2. However, we also specify $f(\alpha_{st})$ as a cubic for Model 2 to facilitate model comparisons. This assumption does not qualitatively alter the results (as we shall see). The F -tests for Model 1 were as follows: linear vs. quadratic, $F_{1,\infty} = 14.7$; linear vs. cubic, $F_{2,\infty} = 10.2,$ quadratic vs. cubic, $F_{1,\infty} = 5.7.$

First, Eq. (9) is estimated with the restriction $\lambda_1 = \lambda_2 = \lambda_3 = 0$ to recover estimates $\{\hat{\beta}_t, \hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3\}$.[22] Then instrumented vessel shares are

$$\tilde{\alpha}_{st} = \frac{1}{N}\sum_{i=1}^{N}\tilde{p}_{ist},$$

where,

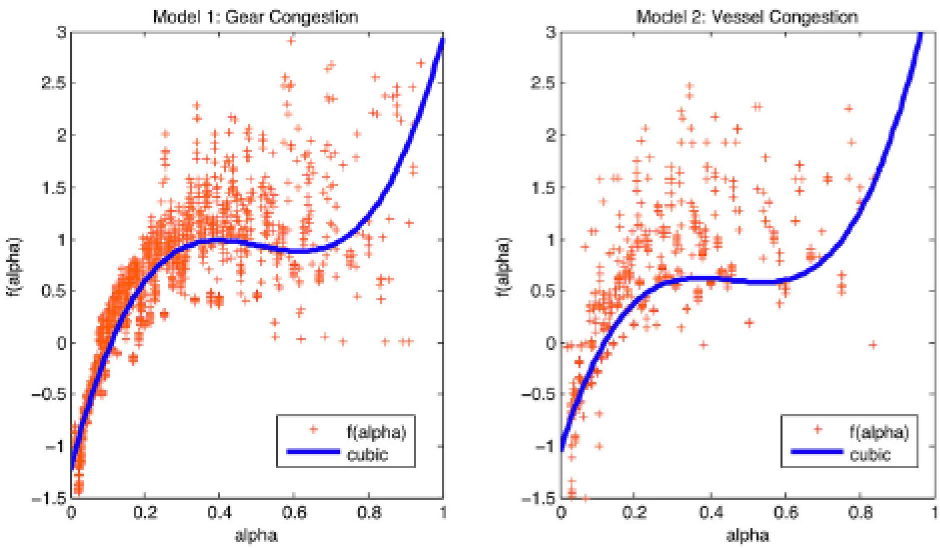
$$\tilde{p}_{ist} = \frac{\exp\left[\hat{\beta}_t + \hat{\beta}_1 REV_{st} + \hat{\beta}_2 STDV_{st} + \hat{\beta}_3 BYCATCH_{st} + \hat{\gamma}\, DISTANCE_{ist}\right]}{\sum_{j=1}^{S}\exp\left[\hat{\beta}_t + \hat{\beta}_1 REV_{jt} + \hat{\beta}_2 STDV_{jt} + \hat{\beta}_3 BYCATCH_{jt} + \hat{\gamma}\, DISTANCE_{ijt}\right]}, \quad (13)$$

and where $\hat{\gamma}$ is the estimate from the original likelihood function in Eq. (6). Then OLS is used to estimate Eq. (9) with $\tilde{\alpha}_{st}$ substituted for α_{st} in Eq. (10).

Results of the above procedure are in Table 3. The results for Model 1 indicate that all three curvature parameters $\{\lambda_1, \lambda_2, \lambda_3\}$ are significant and imply a non-monotonic interaction, while the results for Model 2 indicate that third-order term is insignificant. Fig. 3 depicts $f(\tilde{\alpha}_{st})$ for both Model 1 (left pane) and Model 2 (right pane). The solid curves are the conditional mean of the shares and the dashed curves are the 95% upper and lower confidence bounds, based on the standard errors in Table 3 (left two columns). For Model 1 there are two points in the curve where the estimated $f'(\tilde{\alpha}_{st}) = 0$ when $\tilde{\alpha}_{st}$ equals 0.3565 and when it equals 0.6066. When less than 35.65% of vessels visit a site on a given day, there

[21] Although we directly address the correlation between αst and ηst in our IV estimation, we do not explicitly investigate two other forms of correlation within the data: serial correlation and spatial correlation. Both of these forms of correlation may be important considerations which we plan to more formally investigate in future research.

[22] In their linear setting, Timmins and Murdock (2007) impose the restriction λ2 = λ3 = 0, letting endogenous congestion enter into the first-stage regression. Our restriction does not affect consistency of their procedure, but letting λ1 be a free parameter in our first-stage produced nonsensical results. Our sense is that congestion endogeneity is severe in this setting, and including it in the first stage is= possibly biasing our results.



Crosses are estimated values of f. Cubic curve is fit using MATLAB Basic Fitting algorithm.

Fig. 2. Semi-parametric $f(\alpha_s)$, endogeneity ignored.

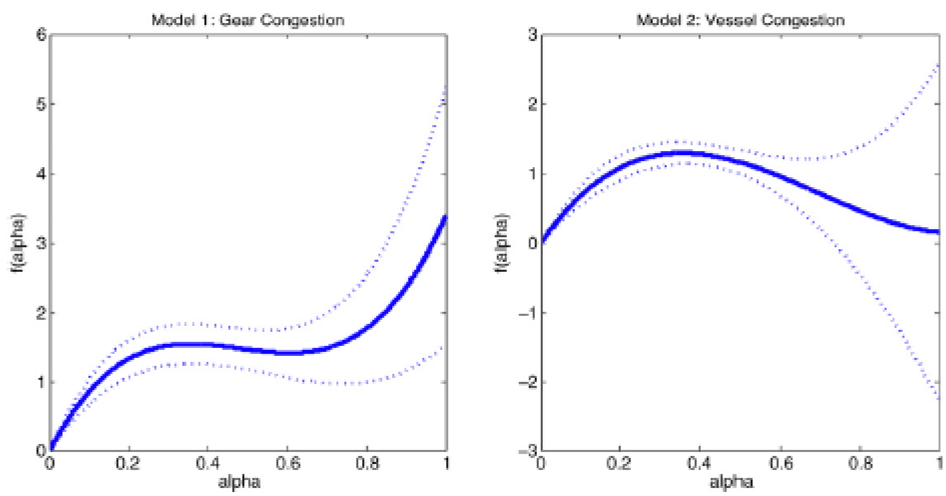


Fig. 3. Final third-order polynomial estimate of $f(\bar{\alpha}_s)$: dashed lines are 95% confidence intervals.

are agglomeration effects, but, when 35.65% to 60.66% of vessels visit, there are congestion effects. Finally, when $\bar{\alpha}_s$ is beyond 60.66%, vessels will, again, agglomerate.[23] For Model 2 the two inflection points are when gear deployment shares, $\bar{\alpha}_s$, equals 0.3573 and 1.0349, the latter lying outside of the range of feasible values for $\bar{\alpha}_s$ and outside the x-axis in the second panel of Fig. 3. If one were to set the third-order term equal to zero, due to its statistical insignificance, the feasible inflection point is then 0.2656.

Robinson's (1988) semi-parametric estimator of $f(\alpha)$, using the instrumented shares $\bar{\alpha}_s$, generates very similar results to the parametric model. These results are in the last four columns of Table 3. The coefficients on the revenues (β_1) and its standard deviation (β_2) are statistically significant at conventional levels for both Models 1 and 2, and the coefficient on bycatch (β_3) is not. Fig. 4 depicts the semi-parametric interaction function using instrumented shares for both Model 1 (left pane) and 2 (right pane). A cubic function was fit to the both the data for Model 1 (solid curve in the left pane) and Model 2 (dashed curve in the right pane) using MATLAB's curve fitting routine. Also, a quadratic function was fit to Model 2 (solid curve in right pane), because the third-order term of the

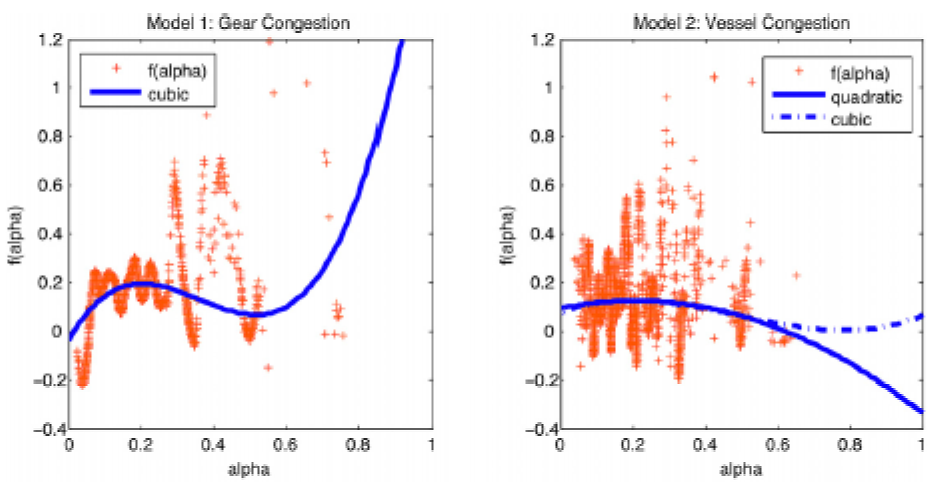
[23] While it is technically an inconsistent estimation procedure due to the nonlinearity of f , estimation of the semi-parametric model using instrumented (vs. actual) shares produces a similarly shaped, non-monotonic function that is not presented here.

polynomial in the parametric model was insignificant (Column 2 in Table 3). Calculating the inflection points for the semi-parametric model using instrumented shares, Fig. 4 shows that agglomeration is present up until the shares equal to 0.2049 in Model 1 and 0.1965 in Model 2 (0.2077 if using the quadratic function for Model 2). Beyond this point, sites exhibit congestion

Table 3
Final IV estimates: standard errors indicated in parenthesis.

	Parametric		Semi-parametric			
Parameter	Model 1	Model 2	Model 1	Model 1 Bandwidth	Model 2	Model 2 Bandwidth
γ	−0.0280** (0.0077)	−0.0136 (0.0114)	–	–	–	–
β_1	0.0061** (0.0029)	0.0059** (0.0021)	0.0058* (0.0030)	0.0090	0.0053** (0.0019)	0.0530
β_2	−0.0075** (0.0024)	−0.0039** (0.0011)	−0.0093** (0.0016)	0.0040	−0.0052** (0.0007)	0.0018
β_3	0.0009 (0.0032)	0.0016 (0.0022)	0.0030 (0.0041)	0.0087	0.0026 (0.0027)	0.0027
λ_1	10.77** (2.4794)	8.24** (2.0360)	–	–	–	–
λ_2	−23.99** (6.9262)	−15.51** (7.1606)	–	–	–	–
λ_3	16.61** (6.3025)	7.43 (7.5553)	–	–	–	–

* Indicates significance at the 90% level.
** Indicates significance at the 95% level.



Crosses are estimated values of f. Cubic curve is fit using MATLAB Basic Fitting algorithm.

Fig. 4. Semi-parametric $f(\tilde{\alpha}_{st})$, using instrumented shares.

until the shares reach 0.5181 in Model 1 and 0.7865 on Model 2, at which point agglomeration again arises.

Fig. 5 shows the distribution of $\tilde{\alpha}_{st}$ resulting from the sorting equilibria for both Models 1 (left pane) and 2 (right pane). For parametric Model 1 a majority of the distributional mass, approximately 95%, lies below the initial inflection point of the parametric cubic function (0.3565) and only 0.23% of the mass lies above the second inflection point (0.6066). For the non-parametric Model 1 approximately 24% of the mass lies above the initial inflection point of 0.2049 and only 0.45% lies above the second inflection point (0.5181). Combined these results suggest that agglomeration effects dominate for Model 1 with between approximately 5% and 24% of the data exhibiting congestion. For Model 2 a similar pattern arises. Approximately 95% of the distributional mass lies below the initial parametric inflection point of 0.3573 while approximately 70% lies below the initial semi-parametric inflection point of 0.1965. Furthermore, none of the distributional mass lies above the second non-parametric inflection point of 0.7865. Therefore, as was the case with Model 1, vessel agglomeration dominates the data, with congestion observed for approximately 5%–30% of the data, depending on the whether or not one focuses on the parametric or semi-parametric results.

Although the last segment of behavior for Model 1 (that lying the right of the second parametric or non-parametric inflection points in the left pane of Figs. 3 and 4, respectively) is inconsistent with a (quasi-) concave interaction function, the curve estimates in this region are based on relatively few observations for which crowding was particularly intense. Consequently, the true interaction function may still be (quasi-) concave.[24] Alternatively, these extreme observations could be the result of complex herding behavior (Bikchandani et al., 1992) in which the private vessel's signal of stock abundance is outweighed by the public information provided by the observed behavior of the other vessels. However, private information is inconsistent with our complete information model.

In summary, the empirical results suggest a non-monotonic interaction function. Therefore, both agglomeration and congestion effects are present in the strategic behavior of vessels in the yellowfin sole fishery. There are a number of reasons why vessels

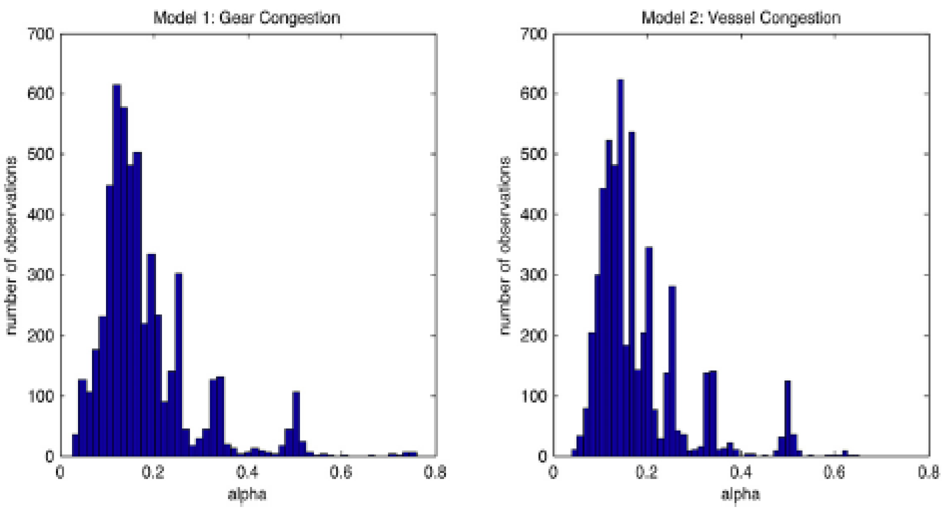


Fig. 5. Histogram of instrumented shares $\tilde{\alpha}_{st}$ for Model 1 (left pane) and Model 2 (right pane).

may wish to fish in regions where other vessels are located. Safety was mentioned in the introduction as a potential motivation for agglomeration. Additionally, if vessels tend to fish in the same regions, it reduces their exposure to the economic risk of deviating from the behavior of everyone else in the fishery and potentially earning less relative to others in the fleet. Therefore, agglomeration is consistent with risk-adverse spatial fishing behavior.[25] In addition, the concave portion of $f(\alpha_{st})$ suggests that the benefits of agglomeration are eventually mitigated. This may be consistent with the notion of serial depletion in fisheries. Serial depletion arises when repetitive fishing in a site lowers catch on subsequent hauls. Therefore, although there are agglomeration effects, they may be diminishing, because too many fish are likely to be taken.

4. Conclusions

This research expands the global game with strategic substitutes and complements of Karp et al. (2007) to a spatial decision model of where to harvest a resource when non-monotonic congestion and agglomeration effects may be present. The theoretical game presented is empirically investigated using data from the BSAI flatfish fishery to determine the extent of strategic substitutes and complements present. Result suggest non-monotonicity of the interaction function. Focusing only on models where we instrument the share of activity in each location and time period, our parametric results suggest that an agglomeration effect arises in the BSAI flatfish fisherywhen the share of vessel/gear activity is below approximately 36%, but beyond this point a congestion effect appears up to approximately 61%, at which point the agglomeration effect once again arises (note that the second inflection point for Model 2 lies outside of 100% and is infeasible). This said, it is important to note that only rarely is it the case that observed share of activity exceeds approximately 61% in the data (see Fig. 5). Our non-parametric results indicate that agglomeration effects are not as persistent as is implied by our parametric model; agglomeration effects exists only until the share of activity reaches 20%. Beyond 20%, a congestion effect exists until the share of activity reaches about 52% (79% for Model 2). However, as was the case with our parametric model, very little of the shares' distributional mass lies beyond the 52% share point, indicating that the reappearance of the agglomeration

[24] Particularly for the non-parametric Model 1 in the left pane of Fig. 4. One could also imagine that curve estimates near the right-most boundary of the support are naturally more biased than those on the interior of the support.

[25] Knowing that other vessels are fishing in a location may also provide a positive signal on the abundance of fish within that region, but this argument is not consistent with our model, since this is less of a response to crowding and more of a response to market signal. If this were true it would suggest the market signal is observed with uncertainty.

effect occurs for only a small portion of the data (very infrequently). Therefore, our overall results (both parametric and non-parametric) indicate that the interaction function is nonmonotonic in agglomeration/congestion in this fishery and is, perhaps, (quasi-) concave.

Although this research has improved our understanding of spatial choice theory and the empirical characterization of sorting equilibrium modeling, it does leave a number of unanswered questions which will be investigated in future research. One of the more important unanswered questions is how might one precisely characterize equilibria within an empirical model with 71 locational choices? Given the structure of the empirical model, it is not feasible to characterize all the equilibria in the data. Finding a practical way to do this for all sites in the analysis might strengthen the connection between the theory and the empirics. Furthermore, a more complete understanding of these equilibria would inform resource management policy, because regulations based on spatial location are commonly enacted in many US fisheries. However, as previously mentioned, this may require a generalization of the theory to the case where ‘‘not fishing’’ is a possible action.

Acknowledgments

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