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Spatial Competition with Changing Market Institutions

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RESOURCES FOR THE FUTURE

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Abstract

The nature of competition across space can be fundamentally altered by changes in market institutions. We propose a new framework that allows for the inclusion of market-altering policy changes in the spatial analysis of competitive behavior. This paper fills a gap in the literature between work that focuses on spatial price responsiveness of agents to one another and the literature that explores how policy changes in market regulations affect the competitive behavior of agents. Specifically, we account for how a change in fisheries management (the creation of catch shares) affects the spatial responsiveness of fish processors across a 21-year time period. We also introduce a method that allows for the incorporation of breaks of explanatory variables in spatial panel data sets.

Key Words: spatial econometrics, spatial competition, market power, fishery management

JEL Classification Numbers: C2, L0, D4, Q2

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Introduction

The economy of the modern world has largely been shaped by the reduction of transportation costs and by changing market institutions (e.g., free trade agreements). Economists have long recognized the role played by space in product pricing and market structure (e.g., Hotelling 1929; Salop 1979; Gabszewicz and Thisse 1979). This understanding has led to a variety of empirical studies that estimate metrics of competition while explicitly accounting for spatial dimensions in terms of both physical distance and product characteristics (e.g., Pinkse et al. 2002; Pinkse and Slade 2004; Hastings 2004; Davis 2006; McMillen et al. 2007). Likewise, analyzing the effects of changes in market regulations and/or information-improving technologies on market competitiveness has had a long-standing tradition in the economics literature.[1] The intersection of these two literatures, particularly in terms of empirical applications, has received far less attention. Surprisingly little quantitative work has been done on a relatively fundamental question about a dynamic economy: how do changes in market institutions affect spatial competition among economic agents? In this paper, we present an empirical methodology and application in an attempt to fill this apparent void in the literature by considering a spatial competition model using a data set with a lengthy time dimension during which a significant regulatory change occurs.

The application that motivates the methodological work developed here is the fundamental change in market structure that is occurring in many of the United States' most valuable fisheries, namely the creation of *catch shares*, or individual fishing quotas (IFQs). After developing our modeling framework, we apply the model to the Alaska sablefish market between fishers (sellers) and the processors (buyers) to whom they sell.[2] Over the time span we analyze,

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[1] See Armstrong and Sappington (2007) for a review of the theory of regulation and Jensen (2007) for a recent empirical application that measures the impact of the introduction of an information cost–reducing technology.

[2] This market is commonly referred to as the *ex-vessel* market.

the management of this species changed from a regulated open-access system, in which fishers competed for shares of the regulator-determined total allowable catch (TAC), to a system in which fishers were granted individual catch shares. The essence of catch shares, or IFQs, is that they end the "race for fish" and create individually allocated shares of the TAC, where the TAC is based on biological surveys and/or other analyses of how to sustainably harvest a portion of the fish populations. With TAC share rights secured, fishers' time costs should decrease in time spent both searching for ports offering relatively high ex-vessel prices and delivering to ports located farther from low-cost fishing grounds.[3] Therefore, the implementation of IFQs also seems likely to affect the spatial competition among ports and thus provides a suitable market for our empirical technique.

Our empirical approach begins under the assumption that price is the strategic variable for competing, but spatially diversified, buyers of a homogenous input. Following a procedure similar to that of Pinkse et al. (2002), we develop best response functions for the buyers and outline the general empirical method used to recover the slope of these best response functions—our proxy for competitiveness. In the case of cross-sectional or panel data over a short time dimension and well-defined market boundaries, the task of estimating the best response function slopes that account for spatial heterogeneity can often be done with a straightforward application of a spatial autoregressive (SAR) model. However, many applied economists are now facing panel data sets with a time dimension of greater duration, such as the one employed in this study. Over longer time dimensions, the market in question could undergo significant changes in market regulation. Such situations call for an amended estimation strategy.

Estimating the best response functions over longer time periods with changes in market regulation presents two obstacles in particular. First, changes in market regulations may change the manner in which firms compete. That is, just as spatial proximity can be fundamental to understanding how entities compete with each other, the nonspatial nature of markets fundamentally affects how agents compete across space. Therefore, the standard SAR model must be amended to include the possibility of a change in spatial competition over time. Accounting for varying spatial competition parameters across cross-sectional groupings has been explored. For example, in a model of college tuition determination, McMillen et al. (2007) allow

[3] Under open access, time spent doing anything other than catching fish reduces the time fishing and therefore the amount of fish caught. Time costs decline with catch shares because the cost of time no longer includes the loss of fish that would have been caught under an open-access system, but rather only the opportunity cost of time.

the spatial component of tuition determination to vary across institutional classes (i.e., private versus public institutions), and in a model of fiscal policy determination, Elhorst and Fréret (2009) allow the spatial component to vary by reelection probability of the governing party. To our knowledge, however, no existing spatial econometric studies account for the changes in spatial competition across time that result from changing market institutions.

In addition to changes in spatial competition resulting from changes in market regulation, parameters of other price-determining variables may also change as a result of the changing regulations. The second challenge in our empirical approach is to account for these additional changes in parameters. Correctly identifying which parameters of the price-determining variables change over the sample observed is important not only in accurately assessing the effect of the variable in question on observed prices, but also in accurately estimating the spatial competition parameters. Unfortunately, although the econometrics literature has given much attention to endogenously determining *where* parameter break locations should be, much less has been written about *which* parameters should be allowed to have a break. Although economic theory may at times be a sufficient guide, this is not always the case. Improperly applying or neglecting a break can significantly impact the magnitude of the perceived impact of a policy. We therefore provide a model selection procedure to determine which parameters, including the parameter on spatial competition, have a break after the regulatory change.

In addition to providing an appropriate scenario for our empirical approach, the Alaska sablefish fishery, as discussed in further detail in below, is one of the earliest and most commercially important fisheries in the United States to have been converted to this type of catch-share management. Other fisheries appear poised to follow suit, and the current administrator of the National Oceanic and Atmospheric Administration (NOAA) has proposed a significant change in fisheries management that would encourage the transition of federally managed fisheries in the United States to catch shares. This is not without controversy as many processors fear that the introduction of catch shares given only to fishers would result in a significant transfer of rents from the processing sector to the fishers. Wilen (2009) provides a broader discussion of the issues related to processor compensation in IFQ management regimes. Matulich et al. (1996) present a theoretical justification of this argument; contrary to these results, Fell and Haynie (2010) find that, although processors experience reduced bargaining leverage with the creation of IFQs, they do retain significant bargaining power. In response to concerns over this potential loss in processor rents, *processor shares* have recently been granted in the Alaska crab fishery, and a share of fishing quota has been granted to processors in the West Coast groundfish fishery.[4]

The competitive issues addressed in this application thus present one of the larger natural resource policy issues currently under public debate. Further, the movement toward catch shares represents one of the most direct and valuable ways in which natural resources economics has been used to effectively address a public policy question. The remainder of the paper is organized as follows. Section 2 introduces the model that we use to analyze how competitors respond across space under a major regulatory change. Section 3 provides details of our application, including information about the Alaska sablefish fishery, the data used, and the creation of spatial weights. Section 4 presents results, and Section 5 concludes.

Model

The model described below closely follows that given in Pinkse et al. (2002); a major difference is that our model is set up such that the buyers, rather than the sellers, price their product noncompetitively. Although our empirical application uses data over a number of time periods without a loss of generality, we restrict the motivating model described in this section to a single-period framework. This restriction is relaxed for the empirical methodology section. Also, although the application of this model will be to a specific ex-vessel market, we leave the description of the model in general terms as the methodology is useful in other markets.

Supply Side

We begin by assuming that in each time period t, K spatially differentiated and perfectly competitive (price-taking) suppliers (fishers) indexed $k = 1,\ldots, K$ supply a homogenous raw product (fish) that is further refined by buyers (processors). The suppliers face (potentially) space- and time-dependent input factors $S_{kt}(z_{kt}, f_t)$, where z_{kt} are nonprice input factors, and f_t are prices for common input factors. For simplicity, we assume that f_t is one-dimensional. Each

[4] Processor shares create an exclusive right for processors in particular locations to be able to process fish. In Alaska crab fisheries, these shares are geographically fixed, whereas in the West Coast groundfish fishery, the harvest quota is given to processors and can be moved anywhere in the fishery.

supplier must decide how it distributes its output among the N buyers, indexed $i = 1,\ldots, N$.[5] Each of the N buyers offers a buyer-specific price p_{it} for the raw product and has (potentially time-varying) buyer-specific characteristics y_{it}. Given that the suppliers are spatially differentiated, the suppliers will have individual profit functions $\pi_{kt}\left(S_{kt}, \tilde{p}_t, y_t\right)$ with price vector $\tilde{p}_t = \left(\tilde{p}_{1t},..., \tilde{p}_{Nt}\right)$ and buyer characteristics $y_t = (y_{1t},\ldots,y_{Nt})$. Aggregating the individual suppliers' profit functions leads to

$$\tilde{\Pi}_t(S_t, \tilde{p}_t, y_t) = \sum_{k=1}^{K} \pi_{kt}(S_{kt}, \tilde{p}_t, y_t) \tag{1}$$

To derive an optimal supply to buyer i, given the price offered by all buyers, we first approximate (1) with a generalized McFadden profit function (Diewert and Wales 1987). To satisfy the homogeneity restrictions of the profit function, we divide second-order price terms by the input factor price f_t. Our generalized McFadden form is

$$\begin{aligned}\tilde{\Pi}_t \approx \Pi_t = \alpha_0 + \left(\sum_{i=1}^{N}\phi_{it}\tilde{p}_{it} + \phi_f f_t\right)\left(a_z' z_t + a_y' y_t\right) + a_1'\tilde{p}_t + a_2 f_t + \sum_{i=1}^{N}\tilde{p}_{it}B_{iz}' z_t + f_t B_{fz}' z_t + \\ \sum_{i=1}^{N}\tilde{p}_t B_{iy}' y_t + fB_{fy}' y_t + \frac{1}{2f_t}\sum_{i=1}^{N}\sum_{j=1}^{N}\gamma_{ij}\tilde{p}_{it}\tilde{p}_{jt}\end{aligned} \tag{2}$$

where the ϕ terms are researcher-specified as shown in Barten and Bettendorf (1989). As in Kristofersson and Rickertsen (2009), we set the ϕ terms to zero.[6] Given this simplification and $p_t = \tilde{p}_t / f_t$, by Hotelling's Lemma the supply function for buyer i is given as

$$q_{it} = \frac{\partial \Pi_t}{\partial p_{it}} = a_i + B_{iz}' z_t + B_{iy}' y_t + \sum_{j=1}^{N}\gamma_{ij} p_{jt}, \quad \forall i \tag{3}$$

Buyer Pricing

Switching now to the pricing decisions faced by the buyers, we assume that the buyers convert the raw product q_{it} into a finished product Q_{it} at a constant rate, $Q_{it} = \rho q_{it}$, and sell the finished product in a competitive market at price $\tilde{P}_t$. On the cost side, we assume that the buyer's marginal cost of converting the q_{it} into Q_{it}, C_{it}, is a linear function of a vector of input factors $\tilde{c}_{it}$,

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[5] The number of fishers and the number of accessible ports may vary from season to season, leading to K_t and N_t. For simplicity in presentation of the model here, we suppress the t subscript and reintroduce the time variation in the empirical methodology section.

[6] Setting ϕ terms to zero is also implicitly done in Pinkse et al. (2002) as they omit these terms from their approximated profit function.

$C_{it} = \psi'\tilde{c}_{it}$, and that the buyer faces a time-invariant fixed cost F_i. This leads to buyer i's profit function as

$$\max_{p_{it}} \left(\rho\tilde{P}_t - \psi'\tilde{c}_{it} - \tilde{p}_{it} \right) q_{it} - F_i \tag{4}$$

As in Pinkse et al. (2002), we assume that ports play a Bertrand–Nash pricing game each period. Substituting (3) into (4) and differentiating (4) with respect to $\tilde{p}_{it}$ leads to the best response function of buyer i

$$p_{it} = R_{it}(p_{-it}) = \frac{1}{2}\left[\rho P_t - \psi' c_{it} - \frac{1}{\gamma_{ii}}\left(a_1 + B_{iz}^{'} z_t + B_{iy}^{'} y_t + \sum_{j \neq i} \gamma_{ij} p_{jt} \right) \right] \tag{5}$$

where $P_t = \tilde{P}_t / f_t$, $c_{it} = \tilde{c}_{it} / f_t$, and p_{-it} represents a vector of all buyer prices except for p_{it}.

Econometric Methodology

The goal of the empirical section is to econometrically estimate (5), and we make several simplifying assumptions to achieve this end. First, as is common in the spatial competition literature (e.g., Pinkse et al. 2002; Pinkse and Slade 2004), we represent all of the terms *other than buyer prices* as

$$\frac{1}{2}\left(P_t - \psi' c_{it} \right) - \frac{1}{2\gamma_{ii}}\left(a_i + B_{iz}^{'} z_t + B_{iy}^{'} y_t \right) = \beta' X_{it} \tag{6}$$

where X_{it} is an h-dimensional vector of observable supply and demand characteristics. The variables used in X_{it} for our particular application are described in detail in the data section below.

To simplify the remaining terms of (5), we note that $-\gamma_{ij}/2\gamma_{ii}$ is proportional to what is commonly referred to as the diversion ratio in the antitrust literature (Shapiro 1996). The diversion ratio in this instance measures the fraction of quantity supplied to buyer i that would be lost to buyer j if buyer i were to lower its price by one dollar. Given that the transport of raw product by suppliers is costly, the diversion ratio is likely to be a function of the geographical proximity of the two buyers. For example, if two buyers are separated by a large distance and production of the raw product is occurring relatively continuously between these two buyers, then we would expect a low diversion ratio, in absolute terms, as these two buyers are not likely to be trying to attract the same subset of suppliers. Conversely, if two buyers are geographically close to one another, the buyers are likely to be competing for the same subset of suppliers, and therefore we would expect a large diversion ratio in absolute terms. Thus, we assume that $-\gamma_{ij}/2\gamma_{ii}$ is a function of the geographical distance between i and j, $\psi(d_{ij})$, where d_{ij} is a measure of distance between i and j. The specific metric for d_{ij} and the form of $\psi(d_{ij})$ can be researcher-specified, and we apply several different forms as described below.[7] In general, however, we can write the simplification of the remaining terms of (5) for all buyers as

$$\sum_{i=1}^{N}\sum_{j=1}^{N}\frac{\gamma_{ij}}{\gamma_{ii}}p_{jt}=\delta W p_t \tag{7}$$

where elements of $W = w(i,j)$ with $w(i,i) = 0$ and $w(i,j) = \psi(d_{ij})$ for $i \neq j$, and δ is an estimated parameter.

Combining (6) and (7) and allowing for unobservable variables, u_t, forms the basis of the estimated equation

$$p_t = \delta W p_t + \beta' X_t + u_t \tag{8}$$

where u_t may be heteroskedastic and/or spatially correlated. For the purposes of this application, we further assume $E\left[u_t \mid X_t\right] = 0$.

Equation (8) is a standard SAR model set in a panel data context. This model has been used in many settings but may potentially be overly restrictive in this application. As discussed above, over time, institutional and/or technological changes may occur that can directly impact the manner in which space affects the competitive relationship among buyers and sellers. In this application, the implementation of IFQs was a significant institutional change that essentially ended the race for fish among fishers and potentially changed spatial competition (i.e., δ may be time dependent). In addition to changing how space matters, institutional and/or technological change can alter operating costs for both buyers and suppliers. With respect to IFQs, secured harvest rights have generally been shown to slow down the rate of fishing in terms of the quantity of fish caught per day (e.g., Homans and Wilen 1997). The reduced fishing rate can lead to improved capital utilization of both fishers and fish processors, thereby altering the cost structure of both the buyers and the suppliers (i.e., β may be time dependent). Finally, agents may enter or exit the market over time. This is not an issue for the supply side of the market in this application because an aggregate supply function is used for that side of the market. However, for the noncompetitive side, the entry and exit of firms alters each individual firm's best response function by creating time-dependent sets of competitors (i.e., W is time dependent).

[7] Pinkse et al. (2002) develop a method to nonparametrically estimate $w(d_{ij})$. Because the focus of this paper is to assess how spatial competition changes over time, we avoid the additional complexity of estimating $w(d_{ij})$ for now and leave this for future research.

To incorporate the time dependency possibilities discussed above, we estimate a less restrictive form of (8) that allows for a one-time break in δ, as well as a one-time break in some, but not necessarily all, of the β parameters. The break occurs in period $t = \tau$, and it is assumed to be known a priori. The less restrictive SAR is given as

$$p_{it} = \delta_1 \sum_{j=1}^{N_t} w_{ij,t} p_{jt} + \delta_2 d_\tau \sum_{j=1}^{N_t} w_{ij,t} p_{jt} + \beta_1^{'} X_{it} + \beta_2^{'} d_\tau X_{it}^{s} + u_{it} \tag{9}$$

where d_τ is an indicator dummy equal to zero if $t < \tau$ and one otherwise, $w_{ij,t}$ is the ij^{th} element of the (potentially) time-dependent W_t, N_t designates the number of buyers operating in period t, and X_{it}^{s} is an s-dimensional vector containing a subset of the elements of X_{it}.

Estimating (9) presents several challenges. First, as with standard SAR models, the spatially lagged dependent variable is potentially endogenous because of the simultaneity in best response functions: if p_{it} is a function of p_{jt}, p_{jt} will often then be a function of p_{it}, creating simultaneous equations endogeneity. To address the endogeneity issues, models with lagged spatially dependent variables are typically estimated by maximum likelihood estimation (MLE), instrumental variables (IV), or generalized method of moments (GMM) techniques.[8] Second, (9) departs from more standard SAR models in that the spatial-lag parameter is (potentially) time varying. SAR models with regime-specific spatial-lag parameters have been estimated by McMillen et al. (2007) in a cross-sectional data context and by Elhorst and Fréret (2009) in a panel data context. Both of these examples also define the regime based on cross-sectional units, whereas the application presented here defines regimes temporally. To deal with the endogeneity of the spatially lagged dependent variable and the regime-specific spatial-lag parameter, we follow the MLE approach described in Elhorst and Fréret (2009). By using an MLE approach, we implicitly assume $u_{it} \sim$ iid N(0, σ^2). We alter the approach of Elhorst and Fréret (2009) to allow the break to occur across time rather than across cross-sectional units, and amend the approach to allow for an unbalanced panel. The resulting log-likelihood function is

[8] See Anselin (1988) for a review of MLE and IV approaches and Kelejian and Prucha (1999) for a review of the GMM approach in standard SAR models. Extensions of these methods to panel data applications can be found in Elhorst (2003) for the MLE approach, Kelejian et al. (2006) for the IV approach, and Kapoor et al. (2007) for the GMM approach.

$$Log\,L = -\frac{\sum_{t=1}^{T} N_t}{2}\ln\left(2\pi\sigma\right) + \sum_{t=1}^{T}\ln\left| I_{N_t} - \delta_1 W_t - \delta_2 D_\tau W_t \right| - \frac{1}{2\sigma^2}\sum_{i=1}^{N_t}\sum_{t=1}^{T}\left(p_{it} - \delta_1 \sum_{j=1}^{N_t} w_t(i,j) p_{jt} - \delta_2 d_\tau \sum_{j=1}^{N_t} w_t(i,j) p_{jt} - \beta_1^{'} X_{it} - \beta_2^{'} d_\tau X_{it}^{s} \right)^2 \tag{10}$$

where T is the number of time periods , I_{Nt} is an (N_t x N_t) identity matrix, and D_τ is an (N_t x N_t) indicator matrix with all zero elements when $t < \tau$ and I_{Nt} otherwise. Parameters δ_1, δ_2, β_1, β_2, and σ are estimated by maximizing (10). As shown in Elhorst and Fréret (2009), (10) can also be altered to include fixed effects (FEs) or random effects (REs). To accomplish this, one needs only to modify the variables in the last term of (10) by the standard demeaning processes described in the FE and RE literature.[9] Given the likelihood of (10), we can also rewrite the symmetric covariance matrix as

$$\begin{bmatrix} \frac{1}{\sigma^2}\tilde{X}^{'}\tilde{X} & 0 & \frac{1}{\sigma^2}\tilde{X}^{'}\mathrm{diag}\left(.,W_t^1,.\right)\tilde{X}\beta & \frac{1}{\sigma^2}\tilde{X}^{'}\mathrm{diag}\left(.,W_t^2,.\right)\tilde{X}\beta \\ - & \frac{\sum_t N_t}{2\sigma^2} & \frac{1}{\sigma^2}\sum_t tr\left(W_t^1\right) & \frac{1}{\sigma^2}\sum_t tr\left(W_t^2\right) \\ - & - & \begin{array}{c}\sum_t tr\left(W_t^1 W_t^1 + W_t^{1'} W_t^1\right) + \\ \frac{1}{\sigma^2}\beta^{'}\tilde{X}^{'}\mathrm{diag}\left(.,W_t^{1'}W_t^1,.\right)\tilde{X}\beta\end{array} & \begin{array}{c}\sum_t tr\left(W_t^1 W_t^2 + W_t^{1'} W_t^2\right) + \\ \frac{1}{\sigma^2}\beta^{'}\tilde{X}^{'}\mathrm{diag}\left(.,W_t^{1'}W_t^2,.\right)\tilde{X}\beta\end{array} \\ - & - & - & \begin{array}{c}\sum_t tr\left(W_t^2 W_t^2 + W_t^{2'} W_t^2\right) + \\ \frac{1}{\sigma^2}\beta^{'}\tilde{X}^{'}\mathrm{diag}\left(.,W_t^{2'}W_t^2,.\right)\tilde{X}\beta\end{array} \end{bmatrix}^{-1} \tag{11}$$

where $\tilde{X} = \left(X, d_\tau X^s\right)^{'}$, $\beta = \left(\beta_1, \beta_2\right)^{'}$, $W_t^1 = W_t\left[I_{Nt} - \delta_1 W_t - \delta_2 D_t W_t\right]^{-1}$ and $W_t^2 = D_t W_t\left[I_{Nt} - \delta_1 W_t - \delta_2 D_t W_t\right]^{-1}$. As with (10), X and X^s values in (11) can be replaced with the appropriately demeaned values to account for FEs or REs.

[9] See Elhorst (2003) and Elhorst (2009) for a discussion of spatial panel data models and the implementation of FEs and REs for these models using an MLE approach.

The final challenge in estimating (9) is to determine which subset of parameters associated with explanatory variables $W_t\, p_t$ and X_t should be allowed to have a structural break. In the case of a major institutional change, such as the one considered in this application, it is reasonable to assume that several, but not necessarily all, parameters will change. Improperly specifying the model by failing to account for these breaks can lead to an erroneous interpretation of results. However, theory alone may not be sufficient to guide the applied econometrician as to which parameters should be modeled with a break. In this case, an endogenous determination of parameter instability is required.

Endogenously determining the subset of time-varying parameters here is not straightforward. As alluded to above, the econometrics literature has been primarily concerned about determining when in time the breaks occur and much less concerned about determining which subset of parameters appear unstable. A rudimentary procedure for finding which parameters have a break is to test each parameter individually for instability (Ireland 2001). As pointed out in Inoue and Rossi (2008), this one-at-a-time procedure can lead to a mischaracterization of the results because repeatedly using structural-break tests in more than one subset of parameters leads to size distortions (i.e., a difference between the nominal level of the test and the rejection probability). An alternative to using structural-break tests to determine the subset of instable parameters is to use an information criteria approach, in which all possible break combinations are estimated and the chosen specification is that which minimizes the information criteria. The advantage of this approach is that information criteria do not suffer from size distortion in the manner that the one-at-a-time test procedure does and can therefore be employed to consistently estimate the subset of instable parameters (Inoue and Rossi 2008).

Although the information criteria approach can be quite computationally demanding because one must estimate 2^{h+1} break combinations, modern computing technology makes this approach feasible for many empirical undertakings. In this particular application, $h = 10$, resulting in 2,048 (i.e., 2^{11}) estimations per spatial weight. In total, the 2,048 estimations took approximately two minutes to complete using an estimation procedure written in Matlab on a desktop computer with a 2.40 GHz processor and 3 GB of RAM.[10] Thus, this subset selection

[10] Reference to trade names, such as Matlab, does not imply endorsement by the National Marine Fisheries Service of NOAA.

approach is feasible and acceptably fast for this application. The chosen information criterion used for this approach in our application was the Bayesian information criterion (BIC).[11]

Application

Alaska Sablefish Fishery Background

To better understand how changing market institutions affect the nature of spatial competition, the empirical model described above is applied to data from the Alaska sablefish ex-vessel market. Sablefish is a commercially important species found primarily in the North Pacific waters off the coast of California up to the Gulf of Alaska and into the Aleutian Islands and Bering Sea. The fishery has been exploited commercially in U.S. and Canadian waters since the early 1900s. In recent years, the annual ex-vessel value for the U.S.-directed sablefish fishery has been well over $100 million, which is comparable to other commercially important species, such as Alaska salmon, Pacific halibut, and Alaska pollock.

The U.S. management of sablefish fishing activity is separated into an Alaskan section and a Pacific states (California, Oregon, and Washington) section, with most landings and value coming from the Alaska sablefish fishery. Within the Alaska sablefish fishery, the stock is managed with five distinct regions that wrap around the Gulf of Alaska and the Aleutian Islands/Bering Sea. In order from east to west, the management regions are Southeast, West Yakutat, Central Gulf, Western Gulf, and Bering Sea and Aleutian Islands (see Figure 1). Prior to the 1995 fishing season, the fishery was under a regulated open-access system, such that each region was assigned a TAC and was open to all fishers until the TAC was met. Beginning with the 1995 season, fishers were granted IFQs based on historical catch records, assuring the fishers a percentage of the annually determined TAC. The IFQs are allowed to be traded, although many restrictions on trading were put into place to ensure that quota holders were actually involved in the harvesting. IFQs were also designated by management region and required that fishers catch fish in the region associated with the region-specific IFQ.[12]

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[11] A variety of model selection criteria could be employed. Here we use the BIC primarily because of the results of the comparative analysis of Hjort and Claeskens (2003) showing the relative weakness of the Akaike information criterion and predictive comparisons by Raftery and Zheng (2003). We recognize that this is an area of active research and that other criteria may be appropriate in various applications.

[12] More about the Alaska sablefish fishery's management history and the biological background of the sablefish species can be found in Huppert and Best (2004), Sigler and Lunsford (2001), and Pautzke and Oliver (1997).

The estimation procedure described above is applied to annual data for the fishery from 1986 to 2006 ($T = 21$). The proposed method is well suited for explaining how competition changes in this fishery for several reasons. First, the transition of the Alaska sablefish fishery management regime from a regulated open-access TAC management system to an IFQ system provides us with a market setting in which a major institutional change has occurred that is likely to cause parameter instability. In addition, the change is near the middle time period of our data set, allowing for a large number of both pre- and post-change data points. Second, sablefish are caught by a relatively large number of vessels and delivered to ports scattered throughout the Gulf of Alaska (see Figure 1).[13] This suggests that the model described above with price-taking fishers and spatially oligopsonistic processors is realistic for this application. Third, because the fishery has a well-established commercial exploitation history, processor siting decisions were typically made long before the initial period of the examined data, removing issues involved with endogenous distances between competing entities. Finally, the primary processed product for this species is a frozen, headed and gutted (H&G) product; thus, processing is more capital intensive than for species with fresh fish markets. Considering this capital intensity and the general remoteness of Alaska, it seems unlikely that explicit modeling of entry deterrence strategies is relevant in this application, but this may be important in other applications.

Data

The dependent variable in (9), p_{it}, is a measure of the price processors pay for unprocessed fish, the ex-vessel price. This variable is based on fish ticket data provided by the National Marine Fisheries Service's Alaska Fisheries Science Center. Fish tickets are essentially sales receipts, issued for each delivery of unprocessed fish, that provide information on the value and quantity of the delivery by species as well as some data on where the fish was caught. To get p_{it}, we first divide the value by the quantity to get a price in dollars per pound. Because there is little to no variation in the ex-vessel price offered by a processor across a year and little to no variation in the ex-vessel price offered by different processors within the same port, we aggregate the ex-vessel price such that it is the average annual ex-vessel price offered in a port (t

[13] The number of annual participants of longline vessels, the type of fishing vessel responsible for the vast majority of sablefish landings in this fishery, varies by year from a high of approximately 1,000 to a low of approximately 400.

indexes year, i indexes a port).[14] Note that in (9), p_{it} is normalized by a fisher input price, f_t. As in other fishery applications (e.g., Kristofersson and Rickertsen 2007, 2009), we normalize the aggregated ex-vessel price by fuel price. The fuel price used is the average annual diesel #2 price provided by the U.S. Energy Information Agency. Prior to the normalization step, both the fuel price and the aggregated ex-vessel price were converted into 2006 real dollar values using the Bureau of Labor Statistics Producer Price Index (PPI), series WPSSOP3000. In addition to these aggregation and normalization processes, we also filtered the data such that we only consider deliveries from longline vessels and those deliveries that were greater than 500 pounds. We include only longline vessels because this sector represents the vast majority of landings; this also allows us to avoid differences in quality issues from fish landed by other gear types, such as trawling.[15] The minimum delivery restriction was imposed to remove all deliveries for which sablefish was not the targeted species of the fisher.[16]

As stated above, the X_{it} vector contains variables explaining processing and fishing costs and characteristics as well as market conditions. To incorporate the impacts of processor costs and characteristics into the model, we include variables that account for the scale of the processors' capacities, labor costs, and output types—*AvgDel*, *Labor*, and *HG70*, respectively. $AvgDel_{it}$, the average delivery size (in 10,000 pounds) reported on a fish ticket for port i in year t, captures changes in the size of deliveries in a port. The $Labor_{it}$ variable, which accounts for processors' labor costs, is calculated by taking the average monthly wage data based on the North American Industrial Classification System code 311712 (Fresh and Frozen Seafood Processing) for Alaska multiplied by the number of months in which harvesting occurred in port i.[17] The *Labor* variable is converted to 2006 dollars by the PPI described above and is divided by 10,000 to make its scale consistent with other variables in the study. $Labor_{it}$ is also normalized

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[14] A similar procedure was undertaken in Pinkse et al. (2002), in which the authors aggregated prices of different firms at the same geographic terminal into a single terminal-specific price.

[15] Over the sample examined, approximately 90 percent of the total quantity of sablefish delivered was caught by longline gear. By port, the average percentage of quantity delivered caught by longline gear over the sample examined is 94 percent.

[16] Our size restriction does not necessarily remove all nontarget species landings, but, based on pricing patterns, this size restriction does remove outliers that are obviously priced under a mechanism that is different from those described here.

[17] Months harvesting is difficult to determine as fishers do not always fish continuously throughout the year. For this application, months harvesting is calculated for each port as the number of days the port receives deliveries divided by thirty.

on the diesel price described above. As stated above, frozen H&G is the most common processed product type and fish are often delivered to the processor already H&G. However, some fish deliveries are made as whole fish, which are sent directly to relatively small fresh fish markets that exist for sablefish. To account for this product type, we created the variable $perHG_{it}$, which denotes the percentage of the quantity delivered to i in year t that is designated as H&G, as stated on the fish ticket. To account for fishing costs and characteristics, we incorporated variables pertaining to the size and capacity of fishing vessels as well as stock abundance and location. Including information about different vessel capacities is important because boats of different sizes can have different harvesting cost structures. To determine the impact of boat length on ex-vessel prices, we created the variable $per60_{it}$, which gives the percentage of total quantity delivered to i in t that comes from boats of 60 feet or less in length.[18]

Also relevant to both processors and fishers is the processors' distance to fishing grounds. To account for this, we created the variable $In250_{it}$. The fishing waters of Alaska have been divided up into *stat6* areas, discrete zones that vary in size from several hundred square kilometers to several thousand square kilometers. On each fish ticket, fishers must list the stat6 zone from which their catch originated. $In250_{it}$ measures the percentage of the total quantity of fish landed at a port i in t that came from stat6 zones the centroids of which are within 250 kilometers of the port.[19] An obvious concern with this variable is that fishers may choose to fish closer to those ports offering a higher price, creating the potential for endogeneity. This concern would certainly be valid for an exploited resource that is uniformly distributed in space. However, fish stocks tend to be dispersed unevenly, and concentrations can vary from year to year. In this sense, the location of fishers relative to processors is primarily exogenously determined by the location of stock concentrations.[20] We proceed under this line of reasoning. In addition to accounting for the location of the stock, we explicitly account for fish abundance by

[18] Sablefish longliners generally come in the form of *freezer longliners* and *catcher boats*. Freezer longliners are typically larger boats (longer than 60 feet) that can stay at sea longer because they are able to freeze their catch on board. Catcher boats are typically 60 feet or less in length and make shorter trips because they are unable to freeze their catch on board. Thus, we used 60 feet as the cutoff length in the *per60* variable to differentiate between the two vessel classes.

[19] We chose the 250-kilometer cutoff because it was large enough to incorporate typical fishing grounds given the species' habitat, yet small enough to reasonably be within the given port's core fishing grounds.

[20] Because the Alaskan sablefish fishery has been established for approximately a century and because there are few choices for where to develop safe ports in the Gulf of Alaska, the ports have essentially no ability to endogenously move in response to changing market institutions.

creating the variable $Biom_{it}$, a measure of the biomass for each management region of the Alaska sablefish fishery. The biomass variable is an estimate of age 4+ biomass (10,000 metric tons) by region as given in Hanselman et al. (2007). Because this is a region-specific variable and the dependent variable is indexed at the port level, $Biom_{it}$ variables are the same for all ports in a given management region for a given year.[21]

To account for market conditions, we include variables describing the conditions in the wholesale market (i.e., the market between processors and first wholesalers) and in the ex-vessel market. The primary wholesale market for the processed product is in Japan (Huppert and Best 2004). To proxy the wholesale market prices, we use an average annual Tokyo Central Wholesale Market price, P^{TCWM}, available online through NOAA's Southwest Fisheries Science Center website.[22] As with the ex-vessel price, this price is converted to real dollars and is normalized by the diesel fuel price described above. For the ex-vessel market, we account for the degree of competition within a port by calculating a yearly Herfindahl–Hirschman Index (HHI_{it}) for each port.[23] We also calculate $perSable_{it}$, which calculates the percentage of the total expenditures a port makes on all species delivered to that port that is sablefish to get a measure of the relative importance of sablefish to a port. These market condition variables, along with all other variables described above, are summarized in Table 1.

Spatial Weights

To estimate (9), we must first specify a distance weighting rule $\psi(d_{ij})$ to calculate a corresponding weight matrix W_t. The distance weighting rule should be set such that it captures an intuitive sense of relevant competitors of processors in a given port i. We applied several different distance weighting rules in this application. The simplest of these weight matrices were the nearest neighbor weight matrices, $W1_t$ and $W2_t$. These weight matrices are formed under the assumption that processors in a port i react to the price(s) offered by the port(s) nearest to i. The elements of $W1_t$, $w1_t(i, j)$, are set such that $w1_t(i, j) = 1$ if port j is the single nearest neighbor

[21] This is somewhat restrictive because ports on the border of a management region will probably have deliveries from multiple regions; thus, designating a management region–specific *Biomass/Boat* variable may not be appropriate. For ports on the borders of management regions, we also tried assigning *Biomass/Boat* variables such that each was the mean of the two bordering regions. This did not alter the results presented in any substantial way.

[22] Data are available at http://swr.nmfs.noaa.gov/fmd/sunee/twprice/jws.htm.

[23] Although economists are occasionally critical of using the HHI in a product-differentiated market, it is completely appropriate to use the HHI in an undifferentiated market, such as the market for raw fish.

(based on Euclidian distance) of port i in year t and $w1_t(i, j) = 0$ otherwise.[24] Similarly, elements of $W2_t$, $w2_t(i, j)$, are set such that $w2_t(i, j) = ½$ if port j is either the nearest or second-nearest neighbor to port i in year t and $w2_t(i, j) = 0$ otherwise.

In some cases where several ports are in relatively close proximity to one another, the nearest neighbor weights may be overly restrictive. Conversely, if the nearest neighbor to port i is beyond any reasonable distance, the nearest neighbor weights might erroneously place weight on other ports' prices. To address these issues, we also used weights based on competitive regions, as in Hastings (2004). For these weight matrices, generically written as WCR_t with elements $wcr_t(i, j)$, weight is given to the prices of those ports that fall within some researcher-defined competitive radius of distance CR from port i. More specifically, given that N_{it} is the number of ports within a distance of CR from port i, we initially define the elements $wcr_t(i, j)$ as

$$wcr_t(i,j) = \begin{Bmatrix} 1 - \dfrac{d_{ij}}{\sum_j d_{ij}}, \text{if } j \text{ is within } CR \text{ of } i \text{ in } t \\ 0, \text{ otherwise} \end{Bmatrix}.$$

This weighting matrix not only effectively excludes direct competition beyond some competitive radius, it also puts more weight on those ports within the competitive radius that are closest to port i. For this application, we tried a range of distances for the competitive radii: CR = 150 to 450 kilometers, in 100-kilometer increments. To account for competition within the competitive radius, we include an additional variable $comps_{it}$, which counts the number of ports within the competitive radius distance of port i for year t. The average $comps_{it}$ value ranges from 3.0 for *W150* to 7.9 for *W450.* Additionally, if a port has no competitors within the competitive radius in t, that port was dropped from the sample for year t as suggested in Bivand and Portnov (2004).

Results

Specification

The first step in estimating (9) is to determine which parameters have a break post-IFQ implementation. As discussed above, this is done by searching over all possible specifications for

[24] Recall that the data set is an unbalanced panel. Therefore, if a port receives no sablefish deliveries in year t, it is not considered a nearest neighbor of any port that did receive sablefish deliveries in year t.

the minimum BIC. As one may suspect, the results of this search process are affected by the inclusion of port-specific effects (i.e., FEs or REs). We therefore first carry out this procedure for each of the eight weighting matrices described above using an FE estimation method. We then test the selected models for random elements and for efficiency of FEs over REs.

Table 2 presents the variables associated with the parameters found to have a break for each of the weight matrices used under the FE estimation. As can be seen from the table, the minimum BIC specification is the same across all spatial weighting schemes, except for *W150*. Importantly, the set of unstable parameters for all weight matrix (*W)* specifications includes δ (the parameter associated with the distance-weighted prices offered by other processors [*WP*]), implying a post-IFQ implementation change in spatial competition.

With respect to the appropriateness of FEs over REs or a pooled estimate, we first tested for the presence of random elements. We use the standardized LM (SLM) test of Moulton and Randolph (1989), updated for unbalanced panel applications as shown in Baltagi (2008).[25] The null hypothesis of the SLM states that there are no REs, and the test statistic, unlike the common Bruesch–Pagan LM test, asymptotically has a standard normal distribution. The results of the SLM test, provided in Table 2, reject the null hypothesis of no REs. We then conduct a Hausman test to gauge the appropriateness of the RE specifications. Results from this test, also provided in Table 2, reject the null hypothesis of consistency of the RE specification at the five-percent level of significance, indicating the preference for FE specification for all specifications.

Parameter Estimates

Table 3 presents the estimation results for each spatial weight matrix. All estimates are based on an FE estimator and include breaks in parameters described in Table 2. Estimates of individual port dummies (i.e., the FEs) have been suppressed because of data confidentiality restrictions. Estimates of the parameters associated with the weighted prices offered by other processors (the δ parameters) are given at the top of Table 3. Each coefficient shows, as hypothesized, an increase in the price-reaction slope post-IFQ implementation. However, the δs do vary across spatial weights, and some general comments can be made about this variation. A compactly defined competitive radius (*W1*, *W2*, *W150*, *W250*) leads to a smaller pre-IFQ price-reaction slope, but, with the exception of the *W150* weight, to a similarly sized post-IFQ

[25] The SLM test is an extension of the commonly used Bruesch–Pagan LM test (Breusch and Pagan 1980).

implementation increase in the slope to those weights with a more broadly defined competitive radius (*W350* and *W450*). The smaller pre-IFQ reaction slope estimates from the smaller competitive radii could occur if these smaller radii do not pick up all relevant port competitors. The similar post-IFQ implementation increases in price reaction slopes across weight specifications indicate that much of the increase in competition for a given port is due to a greater responsiveness to pricing of that port's closest neighbors. In a fishery application, this is logical as the fishers' ability to take fish to distant ports is limited by the perishability of the fish. Also, results from the larger competitive radii (*W350–W450*) appear to be approximately constant, suggesting a stabilizing of the post-IFQ change in competition as the competitive radius continues to increase. Again given the perishable nature of the market's product and the distance-declining nature of the weights, this appears to be a logical result for this model.

Interpretation of the parameters found to be stable across all spatial weights employed is generally straightforward. As expected, increasing the output price for processors (P^{TCWM}) increases the ex-vessel price. Similarly, as a greater percentage of the fish landed at a port comes from fishing zones relatively close to the port (as measured by *In250*) or as labor costs in processing increase (as measured by *labor*), ex-vessel prices decrease because fishers' transportation costs decrease and nonfish-related processing costs increase, respectively. The positive and significant values of the parameters associated with *perSable* (the percentage of a port's total fish expenditures spent on sablefish) indicate that, as sablefish becomes more important for a port (in terms of the percentage value of its raw fish product), the port pays a per-unit premium. The negative value on *perHG* (the percentage of quantity delivered H&G) suggests that processors are willing to pay a premium for fish delivered as whole fish. This is somewhat surprising because it seems likely that a processor would pay a premium for fish that is already partially processed. However, the at-sea H&G cut is done largely to better pack and store the fish while still on boat and not for marketability reasons. At-sea processing may not be done with the same precision as it would be at an onshore processor. Coupling this with the marginal value of the ancillary products available from whole fish delivery, a case can be made for a negative *perHG* parameter. The parameters on the variable *biom* (biomass) are negative for all specifications, as would be expected because a larger *biom* value should lower fishing costs. However, these parameters are statistically significant for only the *W150* and *W350* specifications. Finally, the inclusion of the number of competing ports inside the competitive radius (as measured by *comps*) increases ex-vessel prices as one would expect, though the marginal effect of an additional port in the competitive radius is quite small.

The preferred specification for all weight matrices except *W150* includes breaks in the parameters associated with *HHI* (the Herfindahl–Hirschman Index), *per60* (percentage of boats 60 feet or smaller), and *AvgDel* (average deliveries). Surprisingly, for the *HHI* parameters, all pre-IFQ estimates are positive and significant. One would suspect that a greater concentration in sablefish processing by a given processor within a port (i.e., a larger *HHI*) would lower that port's sablefish price. However, because the *HHI* is a measure of sablefish processing concentration and ports typically process other species as well, the *HHI* in this case may be picking up specialization in sablefish processing. Larger processors may also be more efficient and therefore able to offer higher prices. After IFQ implementation, the *HHI* premium is essentially removed for the weight specifications that showed a break in this parameter. This result bears out in *F*-tests that fail to reject the null of $\beta_{1,HHI} + \beta_{2,HHI} = 0$ for all weight specifications with a break. The decline in the apparent specialization premium post-IFQ implementation seems likely because the lower harvest rates (in terms of pounds of fish landed per day) observed under IFQs could alleviate any efficiency gains brought about by specialization.

For the *per60* variable, we see that the ex-vessel price drops as more of the port's fish comes from boats of 60 feet or less in length. This discount appears to be removed post-IFQ implementation and, indeed, *F*-tests fail to reject the null $\beta_{1,per60} + \beta_{2,per60} = 0$ for all weight specifications showing a break in this parameter. This could potentially be due to a change in the quality of fish being delivered by smaller boats post-IFQ implementation. On the other hand, the break in the *per60* parameter may be due to a level shift in the prices as *per60* is typically relatively constant for a given port across time.[26]

With respect to the size of the average delivery (*AvgDel*), the break in the parameter is more intuitively explained. Before IFQ implementation, the *AvgDel* parameter estimates are negative and statistically significant, which is likely for two reasons. First, without IFQs, fishers are trying to catch as much as possible before the cumulative TAC is met. Consequently, the rate of harvest is large relative to a fishery with IFQs. With relatively high harvest rates, processing capital is more likely to be fully used, and thus capitally constrained processors give a discounted ex-vessel price in areas with large deliveries. Second, because fishers without IFQs are in a "race for fish" they have an incentive to reach their at-sea fish storage capacity, which would reduce

[26] The stability of *per60* was not sufficient to preclude an FE estimator by demeaning.

the number of trips to and from ports but could also have a negative impact on the quality of the fish delivered. The lower quality fish would then fetch a lower ex-vessel price.

The additive effect on the *AvgDel* parameter post-IFQ implementation is consistently positive such that the total effect of *AvgDel* post-IFQ implementation is now near zero for all specifications. This, again, bears out in the *F*-tests that fail to reject the null of $\beta_{1,AvgDel} + \beta_{2,AvgDel} = 0$ for all cases. This appears reasonable because IFQ implementation slows the rate of harvest, potentially leaving processing capital idle. If idle processing capital is costly, processors will not discount larger deliveries and could possibly pay a premium to more fully use the capital. This line of reasoning is consistent with the theoretical model outlined in Matulich et al. (1996). In addition, although both the pre-IFQ and post-IFQ parameter estimates of *AvgDel* are statistically significant and have theoretically consistent signs, the estimates themselves are quite small, suggesting little impact on ex-vessel prices.

Weight Comparisons

Across all weighting specifications, we consistently find the general result of an increase in spatial competition post-IFQ implementation. However, the parameter estimates do vary across weight specification. In particular, the estimation results from the *W1* and *W150* weight specifications appear quite different from the other results. That these weight specifications lead to noticeably different parameter estimates is somewhat expected. For the case of the *W1* results, it is likely that this weight specification neglects the pricing influence of many relevant competitors for areas where the ports are more densely concentrated as this specification only considers the influence of a port's single nearest neighbor. In the *W150* case, we note that the number of observations is approximately 12 percent lower than the full sample. The significant reduction in the sample for the *W150* case compared to the other weighting specifications essentially amounts to conducting the analysis on a different data set, which very likely explains the noticeably different parameter estimates.

Ideally, one would like to select a single weight specification that is appropriate for the application. In practice, however, determining which weight specification and which parameter-break specification provides the best representation of the ex-vessel market in question is not a straightforward procedure. This is particularly true for this application because the sample size, and thus the model selection criterion, are dependent on the weight used. To compare model fit across specifications, we use the standard adjusted-R^2, hereafter R^2, and the $corr^2$ metrics. The $corr^2$ metric is a measure of the correlation between the actual and fitted dependent variable, given as

$$corr^2 = \frac{\left[(p-\bar{p})'(\hat{p}-\bar{p})\right]^2}{\left[(p-\bar{p})'(p-\bar{p})\right]\left[(\hat{p}-\bar{p})'(\hat{p}-\bar{p})\right]} \tag{12}$$

where p is the dependent variable (prices in this application), $\hat{p}$ is a vector of the fitted values, and $\bar{p}$ is the mean value of the dependent variable.

R^2 and $corr^2$ values are given in Table 3 for each weight specification. Not surprisingly given the similarity in the parameter estimates, the R^2 goodness-of-fit metrics are virtually identical across weight specifications. The $corr^2$ metrics are also similar across weight matrices, with the exception of *W150*, which is considerably lower than the other weights. The $corr^2$s also appear to slightly favor the models with intermediate competitive radii (*W250*–*W350*) and the nearest neighbor weight specification.

Because the R^2 and $corr^2$ metrics do not give a clearly defined preferred specification and the primary variable of concern is the effect of the change in management on the price reaction slope, we conduct a counterfactual of sorts using several different spatial weights. The point of the counterfactual is to highlight the increase in ex-vessel price attributed to increasing processor competition. To do this, we calculate a fitted ex-vessel price using the parameter estimates given in Table 3, but assuming that the price-reaction slope (δ) remains constant at the estimated pre-IFQ value (i.e., we assume that $\delta_2 = 0$). We then simply compare the observed ex-vessel price to the fitted ex-vessel price. Table 4 provides a comparison of the mean difference between the quantity-weighted average observed ex-vessel prices and the quantity-weighted average fitted prices described above for the post-IFQ implementation period. Both the average actual price and average fitted price are multiplied by the diesel price series to calculate a nonnormalized price differential. As can be seen from Table 4, the additional responsiveness to competitors' prices brought on post-IFQ implementation accounts for, on average, a \$0.25 to \$0.58 per pound increase in ex-vessel prices (2006 U.S.\$), which is 12–29 percent of the average post-IFQ implementation ex-vessel price. Dropping the *W150* specification, the range of price increases due to additional responsiveness to competitors is even smaller at \$0.25–\$0.33 per pound or 12–16 percent of the average post-IFQ implementation.

A graphical representation of the minimum and maximum price differential for these weight specifications is given in Figure 2. In this figure, we plot the actual average price for each period and the average predicted price assuming that δ remains unchanged for *W350* (minimum price differential) and *W450* (maximum price differential). The figure shows the sizeable gap between the actual and predicted prices post-IFQ implementation. This gap is fairly consistent across the years with IFQs, with the exception of 1998 when a severe downward spike in prices occurred. This downward spike is also noticeable in Tokyo Central Wholesale Market prices.

Conclusion

Changes in market regulations can affect spatial price responses, as well as other price-determining factors. We consider what factors affect competition among buyers across space and how these factors change under a major alteration in market regulation. Accounting for the breaks in spatial competition, as well as breaks in the parameters associated with other price-determining variables, is important to understanding what occurs as a result of the regulatory change. Logically, changing institutions may alter the manner in which input factors affect competition, but determining which parameters should be modeled with a break included is a question for empirical estimation. In this paper, we propose an empirical framework for estimating price response functions that accommodates breaks in spatial responsiveness parameters, as well as in coefficients on other price-determining coefficients, where the selection of parameters modeled with a break is determined endogenously. The paper fills a gap in the literature between work that has focused on spatial price responsiveness of agents to one another and the literature that explores how policy changes in market regulations affect the competitive behavior of agents.

The empirical methodology is applied to data from the ex-vessel market of the Alaska sablefish fishery to explore how the creation of individual catch shares (i.e., IFQs) affects the manner in which fish processors in this fishery compete across space for the output of fishers. The application has important policy ramifications as catch shares represent one of the most important examples of natural resource economics being used in resource management. Natural resource economists have long realized the problems with common-pool fishery resources and have recognized that creating exclusive use rights can ameliorate these problems. Better accounting for the distributional impacts of this resource management policy is a valuable contribution that will enable policymakers to better anticipate the distributional impacts of the creation of catch shares in other fisheries that are currently considering this policy change.

Although intuition and our general knowledge of competition suggest that competitors close to one another should be more responsive to each other's prices, the manner in which we should incorporate space is not theoretically prescribed. We therefore estimate a number of specifications that include spatial responsiveness to nearest neighbor(s) based on competitive regions of different sizes. We find evidence across all specifications considered of increased spatial competition after the creation of IFQs in the fishery. In addition, we find the differing specifications to be remarkably consistent in terms of both the endogenous selection of parameters modeled with a break and the actual parameter estimates.

We also construct a counterfactual experiment that illustrates how changing competition among processors affects ex-vessel prices. The counterfactual compares the observed price to a predicted price, where the predicted price assumes that the spatial price responsiveness parameter remains at pre-IFQ levels throughout the sample, but allows the other parameters selected to be modeled with a break to change over the sample. In setting up the counterfactual in this way, we can highlight the impact on price of the change in spatial competition in isolation. The results from the counterfactual show that for the best-fitting specifications, the increased spatial competition leads to an average post-IFQ price increase of approximately 12–16 percent.

This framework lends itself to several obvious extensions. For example, in our application, processors sell fish to the Tokyo Central Wholesale Market without monopolistic or oligopolistic power. In other markets, however, the competing buyers may have market power in their finished product markets. The model described above could be amended in a straightforward manner to include such a possibility. Additionally, in our application, we know a priori the timing of the catch-share policy change. Another extension of this methodology would be to endogenously determine the structural break in spatial responsiveness. This would allow this methodology to be extended to uses in which the break is not known, such as in the investigation of collusion. This would significantly expand the possible policy applications of this method. However, applications of this methodology are also valid in a wide range of empirical settings.

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Tables

Table 1. Data Summary

Variable	Mean	Stnd. dev.	Min.	Max.
p (¢/lb)	92.97	31.07	16.40	178.79
HHI	0.82	0.25	0.13	1.00
perSable	0.36	0.25	0.0004	1.00
AvgDel (10,000 lbs)	1.39	1.01	0.03	7.20
P^{TCWM} ($/lb)	5.36	1.27	2.62	7.52
per60	0.91	0.20	0.00	1.00
perHG	0.79	0.22	0.00	1.00
In250	0.80	0.22	0.00	1.00
Labor ($10,000)	2.08	2.33	0.04	14.12
Biom (10,000 mt)	45.23	20.09	17.00	103.00

Notes: This summary is based on the full 543-observation sample. All prices are in 2006 dollars and are normalized on the diesel #2 fuel price as described in the text.

Table 2. FE Specification Break Search Results

Weight	*W1*	*W2*	*W150*	*W250*	*W350*	*W450*
Variable	*Wp*	*Wp*	*Wp*	*Wp*	*Wp*	*Wp*
	HHI	*HHI*	*HHI*	*HHI*	*HHI*	*HHI*
	AvgDel	*AvgDel*	—	*AvgDel*	*AvgDel*	*AvgDel*
	per60	*per60*	—	*per60*	*per60*	*per60*
SLM	26.01**	26.88**	18.98**	20.63**	23.57**	25.21**
Hausman	30.57**	34.66**	43.66**	42.55**	54.69**	62.44**

Notes: Unstable parameters associated with variables are given. For SLM and Hausman test results (**) denotes significant at the 5% level and (*) denotes significant at 10% level.

Table 3. Weight Comparisons

Variable	*W1*	*W2*	*W150*	*W250*	*W350*	*W450*
Wp	0.26**	0.43**	0.35**	0.43**	0.54**	0.55**
DWp	0.11**	0.09**	0.18**	0.08**	0.06*	0.08**
HHI	11.83**	12.15**	9.86**	13.54**	11.65**	12.36**
perSable	10.30**	9.36**	9.44**	9.13**	9.41**	9.52**
AvgDel	–2.39**	–1.82**	–1.60*	–2.19**	–2.03**	–1.97**
P^{TCWM}	11.63**	8.81**	8.87**	8.92**	7.21**	6.62**
perHG	–10.50**	–10.60**	–12.47**	–11.32**	–11.38**	–11.80**
per60	–16.89**	–16.81**	–6.88	–15.07**	–16.03**	–15.16**
In250	–6.13*	–6.59**	–7.67**	–6.35**	–6.51**	–5.86**
labor	–0.91**	–0.87**	–0.59	–0.85**	–0.95**	–0.94**
biom	–0.17*	–0.10	–0.24**	–0.17*	–0.18*	–0.16*
comps	—	—	1.36	1.09	0.98	0.94*
DHHI	–14.85**	–15.30**	–5.04**	–15.62**	–17.34**	–17.56**
DAvgDel	5.14**	4.37**	—	4.69**	4.37**	4.02**
Dper60	20.64**	18.13**	—	20.49**	21.03**	18.90**
BIC:	5.64	5.48	5.54	5.52	5.41	5.40
$corr^2$:	0.64	0.64	0.64	0.64	0.64	0.64
R^2	0.88	0.90	0.89	0.89	0.90	0.90
No. obs.	543	543	480	518	535	539

Notes: (**) denotes significant at the 5% level and (*) denotes significant at 10% level based on *t*-statistics. (—) indicates parameter not included in estimation. *DX* variables indicate that variable *X* is interacted with the indicator dummy d_τ. No. obs., number of observations for each weight matrix.

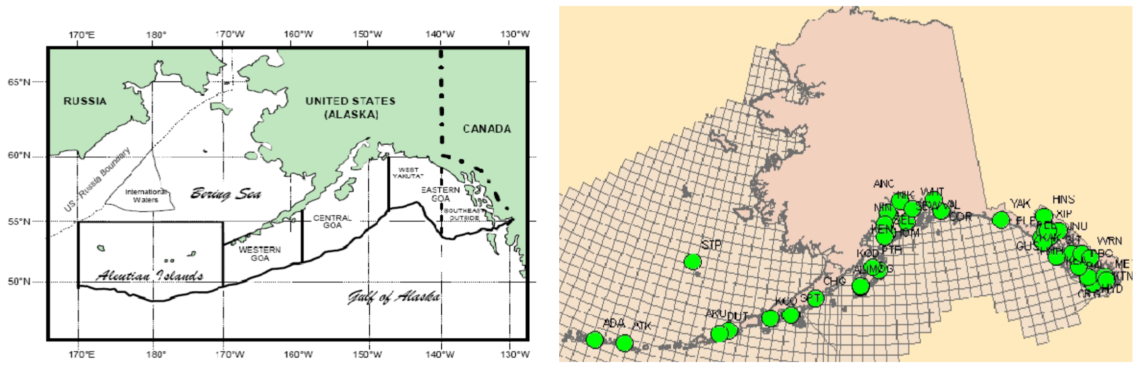
Table 4. Counterfactual Comparison

Weight	Mean($p_{\tau:T} - \hat{p}^1_{\tau:T}$)	% increase
W1	29.2	14.4
W2	33.1	16.3
W150	58.2	28.6
W250	26.3	12.9
W350	25.1	12.4
W450	33.3	16.4

Notes: Mean$\left(p_{\tau:T} - \hat{p}^1_{\tau:T}\right)$ represents the mean difference between the quantity-weighted average ex-vessel price (p_t) and the predicted quantity-weighted average ex-vessel prices over the post-IFQ implementation period (τ:*T*), assuming that δ is constant pre-IFQ implementation ($\hat{p}^1_t$). Differences in prices are given in ¢/lb. % increase is the average percentage difference between p and $\hat{p}^1$ over τ – *T*.

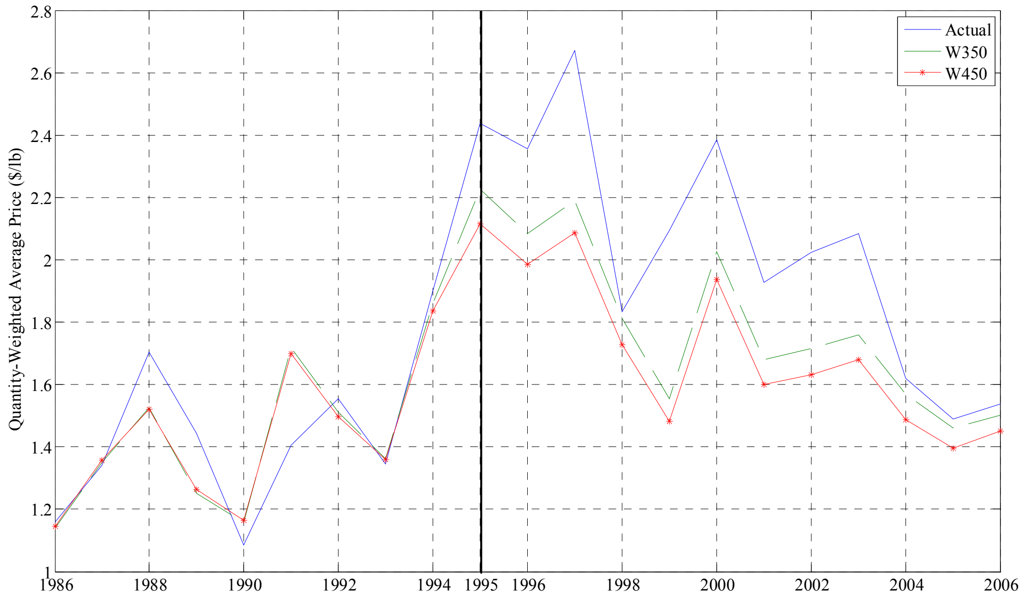
Figures

Figure 1: Sablefish Management Regions and Ports



Notes: Dots on the right-side panel represent ports included in the sample.

Figure 2: Actual versus Constant-*δ* Predicted Prices



Notes: Prices are quantity-weighted average annual prices. *W350* and *W450* predicted prices are based on δ remaining constant at pre-IFQ levels for the entire sample.