Spatial Competition with Changing Market Institutions

Harrison Fell
Fellow
Resources for the Future
1616 P Street NW
Washington, DC 20036
phone: 202-328-5005
fax: 202-939-3460
email: fell@rff.org

Alan C. Haynie
Economist
National Oceanic and Atmospheric Administration
National Marine Fisheries Service
Alaska Fisheries Science Center, Sand Point Laboratory
7600 Sand Point Way NE, Building 4
Seattle, WA 98115
phone: 206-526-4253
fax: 206-526-6723
email: Alan.Haynie@noaa.gov

Abstract

Competition across space can be fundamentally altered by changes in market institutions. We propose a framework that integrates market-altering policy changes in the spatial analysis of competitive behavior and incorporates endogenous breaks in explanatory variables for spatial panel datasets. This paper fills a gap in the literature between work focusing on spatial price responsiveness of agents and work on changes in market regulations that affect competition. We apply the framework to an important current fishery managment policy to explore how a change from aggregate to individual fishing quotas (IFQs) affects the spatial price responsiveness of fish processors.

Key Words: spatial econometrics, spatial competition, market power, fishery management
JEL Classification Numbers: C2, L0, D4, Q2

Spatial Competition with Changing Market Institutions

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 estimate 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'

---

[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.

largest and 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 processors (buyers) to whom

fishers sell, commonly referred to as the ex-vessel market. Over the time span we analyze,

the management of this species changed from a regulated open-access system, in which

fishers competed from a common pool of total allowable catch (TAC) which is based on

biological surveys and other analyses, to a system in which fishers were granted IFQs. The

essence of the IFQs is that they end the "race for fish" by creating individually allocated

shares of the TAC. With fishing 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.[2] Therefore, the implementation of IFQs

also is likely to affect the spatial competition among ports and thus provides a suitable

market for our empirical technique.

In addition to providing an appropriate scenario for our empirical approach, the

Alaska sablefish fishery 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. A variety

of other fisheries are following suit, and the National Oceanic and Atmospheric

Administration (NOAA) has recently proposed a significant change in fisheries

---

[2] Under open access with a large number of fishers, time spent doing anything other than catching fish reduces the time an individual fishes and therefore the amount of fish they catch. 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 that comes from prolonging the time it takes to catch the vessel's share of the TAC.

management that would encourage the transition of 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. Matulich et al. (1996) present a theoretical justification of this argument.[3] 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 degree to which policies protecting processors' interests are warranted depends largely on determining how IFQs will alter competition among processors, which is the central question addressed here.

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

---

[3] In an alternative analysis, Fell and Haynie (2010) show, through an empirical example, that IFQs may lower processors bargaining power, but not necessarily to the point of complete rent extraction. Wilen (2009) also cast doubts as to whether or not the assumptions necessary to generate the complete rent-extraction results of Matulich et al. (1996) are realistic.

[4] Processor shares create an exclusive right for processors in particular locations to be able to process fish which achieves social goals of community preservation at the potential cost of market distortion. 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 so finacially compensates processors but does not distort markets or necessarily preserve processor-based communties. For more on other systems of processor compensation under IFQ management see Wilen (2009).

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. First, changes in market regulations may alter 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 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. While the econometrics literature has given much attention to endogenously determining *where* parameter break locations should be, but much less has been written about *which* parameters should be allowed to have a break. In some situations, economic theory may be a sufficient guide to determine which parameters should be modeled with a break, though this is not always the case. Because improperly applying or neglecting a break can alter the magnitude of the perceived impact of a policy, we provide a model-selection procedure to determine which parameters, including the parameter on spatial competition, have a break after the regulatory change.

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 resource 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, offer prices for the raw (unprocessed) 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 vector of input factors $S_{kt} = [z_{kt}, f_t]'$, where z_{kt} are non-price input factors, and f_t are prices for common input factors. For simplicity, we assume that f_t is one-dimensional. Each 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 $\pi_{kt}(S_{kt}, \tilde{p}_{kt}, y_t)$ with price vector $\tilde{p}_t = (\tilde{p}_{1t},\ldots, \tilde{p}_{Nt})$ and buyer characteristics $y_t = (y_{1t},\ldots,y_{Nt})$. Aggregating the individual suppliers' profit functions leads to

---

[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.

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

where $S_t = [S_{1t}, \ldots, S_{kt}]$.

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

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

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

$$q_{it} = \frac{\partial \Pi_t}{\partial p_{it}} = a_1 + z_t B_{iz} + y_t B_{iy} + \sum_{j=1}^{N} \gamma_{ij} p_{jt}, \quad \forall i \tag{3}$$

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

---

[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.

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

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

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 $\tilde{p}_t$ leads to the best response function of buyer i

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

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

$$\frac{1}{2}(\rho P_t - c_{it}\psi) - \frac{1}{2\gamma_{ii}}(a_1 + z_t B_{iz} + y_t B_{iy}) = X_{it}\beta \tag{6}$$

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 below in the data section of the paper.

To simplify the remaining terms of (5), Pinkse et al. (2002) 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 value). Thus, we assume that $-\gamma_{ij}/2\gamma_{ii}$ is a function $\psi(d_{ij})$ of the geographical distance between i and j, 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. In general, however, we can write the simplification of the remaining terms of (5) for all buyers as

$$\sum_{i=1}^{N}\sum_{j=1}^{N}\frac{-\gamma_{ij}}{2\gamma_{ii}}\,p_{jt}=\delta W p_{t} \tag{7}$$

where $(i,j)^{\text{th}}$ elements of W, w_{ij}, are defined as $w_{ii}=0$ and $w_{ij}=\psi(d_{ij})$ for $i\neq j$, and δ is an estimated parameter. [7]

---

[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.

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

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

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

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., an unbalanced panel means W is also time-dependent).

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

$$p_t = \delta_1 W_t p_t + \delta_2 d_\tau W_t p_t + X_t \beta_1 + d_\tau X_t^s \beta_2 + u_t \tag{9}$$

where d_τ is an indicator dummy equal to zero if $t < \tau$ and one otherwise, W_t is the $N_t \times N_t$ (potentially) time dependent weight matrix, p_t is a N_t vector of prices, and X_t^s is an $N_t \times s$ matrix containing a subset of the elements of X_t.

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. 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. Both of these examples also define the regime based on cross-sectional units, whereas the application presented here defines regimes temporally. 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 implementation of IFQs considered here, it is reasonable to assume that some

but not necessarily all parameters will change. Improperly specifying the model by failing to account for these breaks or simply assuming all parameters are time-varying can lead to an erroneous interpretation of results.

To deal with the endogeneity issue and potential time-varying spatial lag parameter we estimate (9) using a generalized method of moments (GMM) approach with fixed effects (FE). Alternatively, we could use employ the spatial panel maximum likelihood estimation (MLE) approach (see Elhorst 2003). Unfortunately, the MLE approach is only consistent under the often overly-restrictive assumptions that the errors are both normally distributed and homoskedastic. The GMM approach provides consistent parameter estimates even if these assumptions fail. The disadvantage of the GMM approach, beyond being less efficient if the errors meet the conditions necessary for consistency with an MLE approach, is that one must have suitable instruments for the endogenous spatially weighted prices. We discuss our instrument approach in more detail below.

Endogenously determining the subset of time-varying parameters here is not straightforward. As noted 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. One could simply circumvent this break search exercise and model the best response equation with a break in all right hand side variables. However, as discussed in Elhorst (2009), adding or dropping explanatory variables can greatly change the estimated spatial response (δ_1 and δ_2). Without further theoretical or statistical justification to support a model with a break in all explanatory variables, inference on spatial responses is potentially incorrect. In terms of searching for the proper specification, 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 (2010), 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 2010).

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, $h = 9$,

resulting in 1,024 (i.e., 2^{10}) estimations per spatial weight. In total, the 1,024 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.[8] Thus, this

subset selection approach is feasible and acceptably fast for this application. The chosen

---

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

information criterion used for this approach in our application was the Bayesian information criterion (BIC).[9]

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 (also referred to as 'black cod') 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 in U.S. and Canadian waters since the early 1900s and in recent years, the annual ex-vessel value for the U.S.-directed sablefish fishery has been well over $100 million.

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 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 that was open to all fishers until

---

[9] 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.

the fleet-wide TAC was caught. Beginning with the 1995 season, fishers were granted IFQs based on their historical catch, 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.[10]

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).[11] 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, decisions about where to build processors

---

[10] 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).

[11] 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.

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 and processing is therefore 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 delivered fish, the ex-vessel price, which comes from the Alaska Department of Fish and Game (ADF&G) fish ticket data. Fish tickets are issued for each delivery of fish and are essentially sales receipts that provide information on the value and quantity of the delivery by species as well as some data on where the fish was caught.[12] To get p_{it}, we first divide the value by the quantity to get a price in dollars per pound. Because there is essentially no variation in the ex-vessel price offered by a processor across a year and very little 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 indexes year, i indexes a port).[13] Note that in (9), p_{it} is normalized by a fisher input price, f_t. As in

---

[12] Some fish are caught, processed, and frozen on-board catcher processors that sell directly to the wholesale market. These transactions occur outside of the market between inshore processors and the vessels that deliver to them, so are not part of this analysis.

[13] On average, over 94 percent of the fish delivered to a port in a year receives the same price (¢/lb). Given this lack of price variation across processors within a port and within a year at a given port, we use port-annual prices.

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 trawl gear.[14] The minimum

delivery restriction was imposed to remove all deliveries for which sablefish was not the

targeted species of the fisher.[15]

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

[14] Over the time period of our sample, 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.

[15] 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.

Labor$_{it}$ variable, which accounts for processors' labor costs, is calculated by taking the average monthly earning 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* to give us a seasonal labor cost.[16] 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 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 control for 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.

---

[16] Many fishery employees are paid by the season, so we have converted average monthly pay into a seasonal pay. 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.

Also relevant to both processors and fishers is the processors' distance to fishing grounds. To account for this, we created the variable $ln250_{it}$. 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. $ln250_{it}$ 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.[17] 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.[18] We proceed under this line of reasoning. In addition to accounting for the location of the stock, we explicitly account for fish abundance by 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

---

[17] 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.

[18] Because the Alaska 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.

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.[19]

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.[20] 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.[21] We also calculate $perSable_{it}$, which calculates the percentage sablefish of the total expenditures a port makes on all species delivered to that port to measure of the relative importance of sablefish to a port.

Table 1 provides a summary of the dependent and independent variables over the full sample and for the pre- and post-IFQ implementation subsamples. The summary table shows that many of the have quite sizeable changes after IFQs are implemented. Indeed, the *t*-statistic on the difference between the pre- and post-IFQ subsample means shows that the

---

[19] 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 *Biom* variable may not be appropriate. For ports on the borders of management regions, we also tried assigning *Biom* variables such that each was the mean of the two bordering regions. This did not alter the results presented in any substantial way.

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

[21] 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.

means are statistically different from one another for all variables. This finding supports the notion that the introduction of IFQs fundamentally changed many aspects of the fishery. What remains to be seen is whether the shift in ex-vessel prices is due simply to shifts in explanatory variables or if there was also changes in the relationship between the prices and the explanatory variables.[22]

Spatial Weights

To estimate (9), we must first specify a distance weighting function $\psi(d_{ij})$ 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 six 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 $W1_t$, $w_{ij,t}^1$, are set such that $w_{ij,t}^1 = 1$ if port j is the single nearest neighbor (based on Euclidian distance) of port i in year t and

---

[22] Our estimation procedure is based on the assumption that the data is stationary. Using the panel unit root test of Choi (2002), which had favorable results in a Monte Carlo analysis of panel unit roots under spatial dependence (Baltagi, Bresson, and Pirotte 2007), we reject the null of unit root for p, *AvgDel*, *Labor*, and *Biom*. Based on standard univariate ADF tests, P^{TCWM} failed to reject the null of a unit root. However, when using the test of Kim and Perron (2009), which allows for a level shift in the series, and including a level shift in 1995, we reject the null of a unit root for P^{TCWM}. The remaining variables are bounded by definition and thus we do not test for a unit root. Given the results of the panel unit root tests and the univariate test of Kim and Perron (2009) for P^{TCWM}, we proceed under the reasonable assumption that the data is stationary.

$w^1_{ij,t} = 0$ otherwise.[23] Similarly, elements of $W2_t$, $w^2_{ij,t}$, are set such that $w^2_{ij,t} = \frac{1}{2}$ if port j is either the nearest or second-nearest neighbor to port i in year t and $w^2_{ij,t} = 0$ 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 a 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 $w^{cr}_{ij,t}$, 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 $w^{cr}_{ij,t}$ as

$$w^{cr}_{ij,t} = \begin{cases} 1 - \dfrac{d_{ij}}{\sum_j d_{ij}}, & \text{if } j \text{ is within } CR \text{ of } i \text{ in } t \\ 0, & \text{otherwise} \end{cases}.$$

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 applied a range of distances for the competitive radii: CR = 150 to 450 kilometers, in 100-kilometer increments. Additionally,

---

[23] 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.

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

There are several steps that must be taken in order to obtain estimates of the spatial price responsiveness and its potential post-IFQ change. First, we determine the appropriate specification for each weight considered. Then, we compare the weighting schemes through a series of model fit diagnostics. Finally, we present the results of the weight specifications that fared the best in the weight-comparison step.

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 estimating (9), via GMM with fixed effects, for each possible parameter break specification and then choosing the specification that has the minimum BIC. Again, it is important to note here that we are not searching for the timing of the break, but rather which parameters show instability given the possibility of a break after the implementation of IFQs.

Table 2 presents the results of this BIC-minimizing search procedure. In the table, the parameters associated with the variables given under the corresponding spatial weight headings were found to have a break, while non-listed parameters were constant. As can be seen from the table, the minimum-BIC specification for all weight matrices, except for

W350, includes a break in the parameter on *WP*.[24] Thus, there appears to be evidence of a change in the spatial price responsiveness of processors post-IFQ implementation.

Beyond the apparent instability of the parameter on *WP*, Table 2 shows rather heterogeneous model specifications across each weight. Given this heterogeneity, it is difficult to give economic interpretation to the selected unstable parameters for each weight. Further comparisons of the weights themselves are therefore needed to better select an appropriate specification.

Weight Comparisons

Statistical comparisons of different spatial weighting schemes have been and continue to be an area of considerable research. This particular application poses several interesting and difficult challenges in comparing spatial weights. First, the sample sizes are not the same across all the weights, because more tightly defined competitive regions will exclude some ports. Second, as discussed above, different weight specifications lead to different specification selections in terms of which parameters change post-IFQ implementation. Finally, since the weighting schemes are different, the *WP* and *dWP* variables are different. Thus, none of the models nest any of the other models and simple parameter restriction tests are insufficient to compare models.

In order to deal with the different sample size issue and to make a more direct comparison between weighting schemes, we utilize a cascading comparison approach. This

---

[24] We also updated Elhorst's (2003) spatial panel MLE method to allow for time-varying spatial effects and unbalanced panels and we find the preferred specification for all weights considered includes a break in the parameter on WP. An anoonymous reviewer appropriately expressed concerns that standard MLE assumptions may be invalid, so we have changed our estimation technique to GMM.

approach begins by comparing the *W150* weight, which has the smallest sample, to the

other weights, where the other weights are applied to the *W150*-sample.[25] Next, we

continue on to compare the *W250* weight to the weights *W350*, *W450, W1*, and *W2*, using

the *W250*-sample for all weights. We continue this process of comparing the weight with a

smaller sample to weights with larger samples, all applied to the smaller sample data, until

we get to the *W1* to *W2* comparison, which have the same sample size. Based on this

cascading structure, we can iteratively work toward a preferred weight specification. For

example, if based on the comparison metric, the *W450* weight is preferred to the *W150 –*

W350 weights in each of the three direct comparisons and the *W450* outperforms the *W1*

and *W2* weights when these three weights are applied to the *W450* sample, we would

conclude that the *W450* weight is the preferred weight.

Due to the non-nested nature of the weights, choosing a metric of specification

testing or weight comparison is not a trivial task. Anselin (1988), and more recently

Kelejian (2008), propose using spatial versions of Davidson and MacKinnon (1981)'s *J*-test

to directly compare model specifications. We applied *J*-tests using the bootstrapped method

for critical values as proposed in Burridge and Fingleton (2010). Results from this test lead

to inconclusive results where neither specification in direct comparisons clearly dominated

the other (i.e., the test failed to reject the null regardless of how the null was established).

Anselin (1988) also suggests model selection criterion to compare weights. We therefore

again apply BICs in choosing weights. In addition, we also compare the weights based on

---

[25] When applying the *W250 – W450*, *W1*, and *W2* to *W150*-sample, the break specification process must be
re-run in order to find the preferred specification under each weight.

the root mean squared errors (RMSE) of out-of-sample predictions. To construct the

RMSEs we conduct our cascading comparison approach using data from 1986 – 2004, then

based the RMSEs on the prediction of the ex-vessel prices derived from the estimated

model for 2005 and 2006 compared to the actual observed prices. For this application,

$\text{RMSE} = \sqrt{\left(\frac{1}{Nobs}(p - \hat{p})'(p - \hat{p})\right)}$, where $Nobs$ is the number of predicted observations, p

is a vector of observed prices, and $\hat{p}$ is a vector of predicted prices.

Results from the comparisons are given in Table 3. Based on BICs, the $W450$

weight has a lower BIC than the $W150 - W350$ weights based on direct comparisons. When

comparing the $W450$ weight directly to the $W1$ and $W2$ weights using the $W450$-sample, we

also find that the $W450$ specification leads to a lower BIC. Together, these results indicate

that based on BIC-minimization, the $W450$ weighting scheme is the preferred weight.

The results of the RMSE lead to a slightly different result. As with the BIC, the

$W450$ has a lower RMSE than the $W150 - W350$ weights based on direct comparisons.

However, when comparing the $W450$ results to those of $W1$ and $W2$ when using the $W450$

data, we find that the RMSE of the $W1$ weighting scheme is slightly lower than that of

$W450$. The $W1$ weight also has a lower RMSE than the $W2$ weight when compared under

the full sample. These results indicate that based on out-of-sample RMSE minimization the

preferred weighting scheme is $W1$.

Parameter Estimates

Given the weight comparison results above, we present the estimation results from

the $W450$ and $W1$ weighting schemes in Table 4. As discussed above, all estimates are

based on a GMM estimation method with fixed effects. The instruments used for the

endogenous *WP* and *WdP* variables are *WX*.[26] For each weight matrix, the estimated

specification included breaks in parameters described in Table 2. Estimates of individual

port dummies (i.e., the FEs) have been suppressed for brevity and because of data

confidentiality restrictions.

As discussed in LeSage and Pace (2009), the interpretation of parameter estimates

for explanatory variables is not straightforward due to the feedback effects created by the

spatial linkage of dependent variables. To see this mathematically, note that from (9),

$$\partial p_t \Big/ \partial x_{jt} = (I_{N_t} - \delta_1 W_t - \delta_2 d_t W_t)^{-1}(\beta_{1j} + d_t \beta_{2j}) \tag{10}$$

where I_{N_t} is an $N_t \times N_t$ identity matrix, x_{jt} is a particular variable in X_t, and β_{1j} and β_{2j} are

its corresponding parameters (where $\beta_{2j} = 0$ if x_j is not in both X_t and X_t^s). Given this form,

it is clear to see that the impact on price in period t due to a small change in x_{jt} is not simply

the corresponding parameter due to the spatial interaction effects between the ex-vessel

prices. In addition, for this particular example, the impact of a change in an explanatory

variable is also time-varying due both to the possibility of an unstable parameter on the

explanatory variable itself and the unstable spatial responsiveness variable δ which requires

us to extend the direct and indirect effects methodology of LeSage and Pace (2009) to

account for the unbalanced panel and the break in δ. We thus report an average direct and

---

[26] For instrumental variable and GMM estimation approaches in spatial applications, it is also common to include *W*W*X* and possibly *W*W*W*X* to the matrix of instrumental variables. However, in this application, inverting the weighting matrix in the GMM estimation proved problematic with the inclusion of these higher-order weighted explanatory variables in the set of instruments.

indirect effect for each variable over the pre-IFQ and post-IFQ implementation periods.
The average direct effect, interpreted as the average impact of a change in x_{ijt} on p_{it}, is

calculated as $\dfrac{1}{(t_2 - t_1)} \sum_{t=t_1}^{t_2} \dfrac{1}{N_t} tr\left(\frac{\partial p_t}{\partial x_{jt}}\right)$, where t_2 to t_1 is the time span under

consideration and $tr\left(\frac{\partial p_t}{\partial x_{jt}}\right)$ is the trace of (10). The average indirect effect, interpreted as

the mean of the total cross-region impact of a change in x_{ijt}, is calculated as the average sum

of off-diagonal elements $\dfrac{1}{(t_2 - t_1)} \sum_{t=t_1}^{t_2} \dfrac{1}{N_t}\left(1'_{N_t}\left(\frac{\partial p_t}{\partial x_{jt}}\right)1_{N_t} - diag\left(\frac{\partial p_t}{\partial x_{jt}}\right)\right)$, where

$diag\left(\frac{\partial p_t}{\partial x_{jt}}\right)$ are the diagonal elements of $\left(\frac{\partial p_t}{\partial x_{jt}}\right)$ and 1_{N_t} is an N_t-vector of ones.

The parameter estimates of greatest interest in this study are those on the variables
Wp and *DWp* since they inform us about the change in spatial competition post-IFQ
implementation. As can be seen from Table 4, both the spatial lag parameter, δ_1, and the
post-IFQ spatial lag parameter, δ_2, are positive and statistically significant to the ten percent
level or less under the *W450* and *W1* weighting schemes. While the results indicate, as
hypothesized, that the implementation of IFQs increased the spatial competition among
processors in this fishery, the parameter estimates themselves are quite different between
the two models. This is not that surprising, given both the variation between the weights
and the different break specifications. It is also not a given that the different δ's estimates
from these weights will lead to dramatically different results in terms of the post-IFQ
change in ex-vessel price that can be attributed to the change in price responsiveness. A
counterfactual-type analysis, which we discuss in the next section, is needed to answer this
question.

The parameters and corresponding standard errors of most of the remaining explanatory variables are also statistically significant and have the expected signs. For instance, we would expect to find a positive parameter on P^{TCWM} as an increase in wholesale price should increase ex-vessel price and on *perSable* as ports more specialized in sablefish processing should have efficiencies allowing them to offer higher ex-vessel prices. Likewise, a negative parameter on *Labor* is expected since increased labor costs should decrease what processors can spend on fish, while negative parameters on *ln250* and *biom* are as expected since increases in these variables decrease fishers' travel costs and fish searching costs, respectively. It should be noted, however, that for the *W1* weighting case the *ln250* price effect is essentially eliminated post-IFQ implementation. Indeed, the Wald statistic on the restriction that the sum of the *ln250* and *Dln250* parameters is zero ($\beta_{1,\,ln250} + \beta_{2,\,ln250} = 0$) fails to reject this null.

Interpretation of some of the other parameters is not as straightforward. The pre-IFQ *HHI* parameter is positive and significant for both the *W450* and *W1* weights. One might expect that a greater degree of processor concentration in a port (i.e., a larger *HHI*) would allow dominant processors to exercise monopsonistic power and offer lower ex-vessel prices. 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. It is of course also possible that specialization is higher in places where the inherent value of sablefish is higher. 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 Wald tests that fail to reject the null of

$\beta_{1,HHI} + \beta_{2,HHI} = 0$ for both weighting schemes presented.

Likewise, the negative value on *perHG* (the percentage of quantity delivered H&G) suggests, somewhat surprisingly, that processors are willing to pay a premium for less-processed whole fish. 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.[27]

In addition to the parameter values and standard errors Table 4 also provides the Hansen *J*-test of overidentifying restrictions. For both weights, the test fails to reject the null of valid instruments. One might also be concerned with the assumption of exogeneity for the other explanatory variables. Using the *C*-test of orthogonality conditions (see Hayashi 2000), we tested the exogeneity of each explanatory variable in X and X^δ individually. For each variable and across both weighting schemes, we failed to reject the null of exogeneity. We also conducted tests on the subsets of orthogonality conditions on the *a priori* most suspect variables *HHI*, *AvgDel*, and *ln250*. Again, for both weight schemes, we failed to reject the null that this subset of variables is exogenous.

The average direct and indirect effects of the explanatory variables for the pre-IFQ and post-IFQ implementation periods are given in Table 5. For the pre-IFQ period, we find

---

[27] For the *W450* case, the negative pre-IFQ parameter is increased post-IFQ given $\beta_{2, perHG} > 0$. However, $\beta_{1,perHG} + \beta_{2, perHG} < 0$ and the Wald test rejects the null that $\beta_{1,perHG} + \beta_{2, perHG} = 0$.

that the direct effects under both preferred spatial weight specifications are slightly larger in magnitude than the corresponding parameter estimates. Likewise, the post-IFQ direct effects are larger in magnitude than the post-IFQ parameters ($\beta_{1j} + \beta_{2j}$). This is expected given that we have positive spatial feedback effects that become larger post-IFQ implementation. In reviewing the indirect effects, we see that *W450* weight leads significantly larger indirect effects both pre- and post-IFQ compared to the *W1* weight. Again, this is expected for two reasons. First, because the *W450* weight allows for a greater number of spatial interactions than the *W1* weight, we would expect that there to be a larger total estimated spillover effects, and hence larger indirect effects, due to a change in an explanatory variable in a given port. Second, the *W450* case gives a larger spatial interaction effect, δ, than the *W1* case, again leading to larger total spillover effects.

Post-IFQ Spatial Competition Effects

As discussed above, it is difficult to determine from the parameters alone the effect that a change in spatial competition had on prices. To better understand how the change in spatial responsiveness affected the ex-vessel price, we conducted a simple counterfactual analysis. In this counterfactual, we predicted ex-vessel prices assuming that the spatial responsiveness remained at pre-IFQ levels throughout the time-span examined, while allowing parameters determined to be unstable in the break specification step to change post-IFQ. We interpret this predicted price as the expected price in a fishery that implemented IFQs, but with unchanged spatial competition between the processors. We

then compared this counterfactual predicted price to the actual ex-vessel price to determine the effect increased spatial competition had on ex-vessel prices.[28]

Mathematically, the vector of counterfactual predicted prices, $\hat{p}_1$, can be written as $\hat{p}_1 = (I_{NT} - \hat{\delta}_1 W)^{-1}(X\hat{\beta}_1 + X^S\hat{\beta}_2 + \hat{a})$, where I_{NT} is a sample-size dimensioned identity matrix, W is a diagonalized matrix of the W_i's, $\hat{\delta}_1, \hat{\beta}_1, \hat{\beta}_2$ are parameter estimates, and $\hat{a}$ is a vector of the estimated port-specific fixed effects. Figure 2 plots the quantity-weighted average annual ex-vessel prices actually observed, as well as the quantity-weighted average annual $\hat{p}_1$ values for the *W450* and *W1* weights. The figure shows that pre-IFQ implementation (prior to 1995), the average annual predicted prices tracked the actual prices well. Post-IFQ implementation, a sizeable gap opens between the actual and the predicted prices formed under the assumption of time-invariant spatial price responsiveness. It can also be seen that despite the estimation of a larger δ_2 under the *W1* weight than the *W450* weight, the gap between the actual and predicted prices is larger for the *W450* case than the *W1* case. This feature is primarily due to the effect of P^{TCWM} on ex-vessel prices under each weighting scheme. Note in the *W1* case, the parameter on P^{TCWM} is much larger than that in the *W450*. Though not shown here, post-IFQ there was an upward

---

[28] Obviously, similar counterfactuals could be conducted where we hold constant other parameters found to change post-IFQ implementation. However, we maintain our focus on the effects of holding the δ parameter constant because it has a clear economic interpretation. In addition, the change in competition among processors post-IFQ implementation is a major factor in driving current fishery regulation changes, so gaining insight into the possible magnitude of such changes has great practical value.

shift in P^{TCWM}, which pushes up the predicted ex-vessel price from the *W1* model to more than that of the *W450* model.

Table 6 summarizes the counterfactual analysis for all weights in which the break specification step selected models with a post-IFQ change in spatial price responsiveness. The columns under the header "Constant δ" correspond to the counterfactual above. The column labeled "Mean Diff" gives the mean difference between the actual price and $\hat{p}_1$ over 1995 – 2006 (the post-IFQ period). The table shows that this mean difference varies considerably across weights, highlighting the importance of model specification and model selection. The column "% Diff" is the average difference of the actual ex-vessel price from $\hat{p}_1$ during the 1995 – 2006 period in percentage terms relative to the actual price. When viewed in this percentage difference framework and ignoring the largely dominated *W150* weight, we see that prices would have been roughly 25 – 35 percent lower than observed had the spatial price competition not increased, but other parameters were allowed to change. This suggests quite large price effects due to the change in spatial competition.[29]

If we allow δ to change, but keep all the β's constant at pre-IFQ levels ("Constant β" section of Table 6), we see that for the *W150, W250,* and *W450* cases, predicted prices over the period 1995 – 2006 are on average 16 – 35 percent higher than those actually observed. This suggests that the change in the responses to the explanatory variables generally decreased actual prices. For the *W1* model, however, we find essentially no

---

[29] One can also construct counterfactuals for other variables with parameters that change post-IFQ implementation. However, the economic interpretations and policy implications of these counterfactuals are not so clear. Nevertheless, we summarize these counterfactuals in Table 5.

change in the predicted prices relative to the actual prices when we keep the β's constant.[30] This could happen if the change in the parameter is counteracted by a substantial change in the corresponding variable values and/or if the variable has a generally small impact on the price. Both of these issues appear to be at play with respect to the *W1* case. In the final counterfactual, we hold all parameter values at their pre-IFQ levels ("Constant δ and β" section of Table 5). Here we find virtual parity across weights, with all resulting in actual ex-vessel prices that are approximately 22 – 25 percent higher than predicted prices. Importantly though, this result does *not* imply that prices over the period 1995 – 2006 would have been 22 – 25 percent lower without IFQs. This claim cannot be made because many of the explanatory variables themselves changed post-IFQ, likely in response to the new fishing environment under IFQs.

Conclusion

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 empirical methodology presented here 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.

---

[30] The "Constant β's" case is irrelevant for the *W2* case since none of the β's were found to have a break. Although not shown, for the *W350* case we find predicted prices are on average 35¢/lb higher than actual prices for the Constant β's case.

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 neighbor(s) based on competitive regions of different sizes. We find evidence across all but one of the specifications considered of increased spatial competition after the creation of IFQs in the fishery. However, we find that the differing specifications lead to noticeably different parameter estimates as well as the endogenous selection of which parameters are modeled with a break. Given these differences we compare models across spatial weighting schemes based on model selection criteria and out-of-sample prediction power. We find evidence in support of two weighting schemes in particular, the *W1* and *W450* weighting matrices.

In order to illustrate how changing competition among processors affects ex-vessel prices, we construct a counterfactual experiment. 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. In setting up the counterfactual in this way, we can more appropriately isolate the impact that the change in spatial competition had on the ex-vessel prices post-IFQ implementation. 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 25–35 percent.

What is the policy implication of these findings for fisheries management? 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. In some cases, publicly expressed concerns about distribution may be merely an effort to seek rents, but our results suggest that the concern that catch shares will impact the competitive pressures faced by processors is well-founded. A case-by-case examination is required to determine the degree to which this is likely, but there is certainly the possibility that after catch share implementation, processors in neighboring communities will compete more aggressively. Whether or not additional competition is perceived to be beneficial will largely be based on how equitable the current distribution of rents between the processing and harvesting sectors is perceived to be and this will ultimately drive policy design.

References

Armstrong, M., Sappington, D., 2007. Recent Developments in the Theory of Regulation, in: Armstrong, M., Porter, R. (Eds.), Handbook of Industrial Organization. Elsevier, pp. 1557-1700.

Barten, A.P., Bettendorf, L.J., 1989. Price Formation of Fish - An Application of an Inverse Demand System. European Economic Review 33, 1509-1525.

Bivand, R.S., Portnov, B.A., 2004. Exploring Spatial Data Analysis Techniques Using R: The Case of Observations with No Neighbors, in: Anselin, L., Florax, R.J.G.M., Rey, S.J. (Eds.), Advances in Spatial Econometrics: Methodology, Tools and Applications. Springer-Verlag, Berlin.

Baltagi, B., Bresson, G., Pirotte, A., 2007. Panel Unit Root Tests and Spatial Dependence. Journal of Applied Econometrics 22, 339-360

Burridge, P., Fingleton, B., 2010. Bootstrap Inference in Spatial Econometrics: the J-test. Spatial Economic Analysis 5, 93-119.

Choi, I., 2002. Combination Unit Root Tests for Cross-Sectionally Correlated Panels. in: Corbae, D., Durlauf, S., and Hansen, B. (Eds.), Econometrics Theory and Practice: Frontiers of Analysis and Applied Research, Essays in Honor of Peter C.B. Phillips. Cambridge University Press, Cambridge.

Davidson, R., MacKinnon, J., 1981. Several Tests for Model Specification in the Presence of Alternative Hypotheses. Econometrica 49, 781-793.

Diewert, W.E., Wales, T.J., 1987. Flexible Functional Forms and Global Curvature Conditions. Econometrica 55, 43-68.

Elhorst, J.P., Fréret, S., 2009. Evidence of Political Yartstick Competition in France Using a Two-Regime Spatial Durbin Model with Fixed Effects. Journal of Regional Science Forthcoming.

Fell, H., Haynie, A., 2010. Estimating Time-Varying Bargaining Power: A Fishery Application. Economic Inquiry forthcoming.

Gabszewicz, J., Thisse, J., 1979. Price Competition, Quality and Income Disparities. Journal of Economic Theory 20, 340-359.

Hanselman, D., Lunsford, C., Fujioda, J., Rodgvellar, C., 2007. Alaska Sablefish Assessment for 2008, Prepared for NPFMC Bering Sea/Aleutian Island and Gulf of Alaska Stock Assessment and Fishery Evaluation.

Hastings, J.S., 2004. Vertical Relationships and Competition in Retail Gasoline Markets. American Economic Review 94, 317-328.

Hayshi, F., 2000. Econometrics. Princeton University Press, Princeton, New Jersey.

Hjort, N.L., Claeskens, G., 2003. Frequentist Model Average Estimators. Journal of the American Statistical Association 98, 879-899.

Hotelling, H., 1929. Stability in Competition. The Economic Journal 39, 41-57.

Huppert, D., Best, B., 2004. Study of Supply Effects on Sablefish Market Prices, School of Marine Affairs Working Papers. University of Washington.

Inoue, A., Rossi, B., 2010. Which Structural Parameters are "Structural"? Identifying the Sources of Instabilities in Economic Models. Review of Economics and Statistics forthcoming.

Ireland, P.N., 2001. Sticky-price Models of the Business Cycle: Specification and Stability. Journal of Monetary Economics 47, 3-18.

Jensen, R., 2007. The Digitial Provide: Information (Technology), Market Performance, and Welfare in the South Indian Fisheries Sector. The Quarterly Journal of Economics 122, 879-924.

Kelejian, H.H., 2008. A Spatial J-test for Model Specification Against a Single or a Set of Non-nested Alternatives. Letters in Spatial and Resource Sciences 1, 3-11.

Kim, D., Perron, P., 2009. Unit Root Tests Allowing for a Break in the Trend Function at an Unknown Time Under Both the Null and Alternative Hypothesis. Journal of Econometrics 148, 1-13.

LeSage, J.P., Pace, R.K., 2009. Introduction to Spatial Econometrics. Chapmand and Hall/CRC Press, Boca Raton, Florida.

Matulich, S.C., Mittelhammer, R.C., Reberte, C., 1996. Toward a More Complete Model of Individual Transferable Fishing Quotas: Implication of Incorporating the Processing Sector. Journal of Environmental Economics and Management 31, 112-128.

McMillen, D.P., Singell, L.D., Waddell, G.R., 2007. Spatial Competition and the Price of College. Economic Inquiry 45, 817-833.

Pautzke, C.G., Oliver, C.W., 1997. Development of the Individual Fishing Quota Progam for Sablefish and Halibut Longline Fisheries off Alaska. North Pacific Fishery Management Council.

Pinkse, J., Slade, M.E., 2004. Mergers, Brand Competition, and the Price of a Pint. European Economic Review 48, 617-643.

Pinkse, J., Slade, M.E., Brett, C., 2002. Spatial Price Competition: A Semiparametric Approach. Econometrica 70, 1111-1153.

Raftery, A.E., Zheng, Y., 2003. Discussion: Performance of Bayesian Model Averaging. Journal of the American Statistical Association 98, 931-938.

Salop, S., 1979. Monopolistic Competition with Outside Goods. Bell Journal of Economics 10, 141-156.

Shapiro, 1996. Mergers with Differentiated Products. Antitrust 10, 23-30.

Wilen, J.E., 2009. Stranded Capital in Fisheries: The Pacific Coast Groundfish/Whiting Case. Marine Resource Economics 24, 1-18.

Tables

Table 1. Data Summary

Variable	Full Sample		pre-IFQ		post-IFQ		Mean Diff.
	Mean	SD	Mean	SD	Mean	SD	t-stat
p (¢/lb)	92.09	30.73	73.22	19.02	107.77	29.81	16.34
HHI	0.82	0.25	0.79	0.25	0.84	0.24	2.36
$perSable$	0.36	0.25	0.41	0.25	0.32	0.23	4.33
$AvgDel$ (10,000 lbs)	1.40	1.01	1.69	1.20	1.15	0.73	6.17
P^{ICWM} ($/lb)	5.37	1.27	5.17	0.96	5.46	1.57	2.64
$per60$	0.91	0.20	0.95	0.15	0.88	0.23	4.26
$perHG$	0.79	0.22	0.81	0.20	0.77	0.23	2.17
$In250$	0.80	0.22	0.83	0.20	0.78	0.24	2.65
$Labor$ ($10,000)	2.08	2.34	1.32	1.11	2.72	2.84	7.79
$Biom$ (10,000 mt)	44.96	20.32	52.15	22.17	38.97	16.44	7.72

Notes: This summary is based on the full 542-observation sample. SD is the standard deviation. All prices are in 2006 dollars and are normalized on the diesel #2 fuel price as described in the text. Mean Diff. *t*-stat gives the *t*-statistic for the difference in the pre-IFQ and post-IFQ means.

Table 2. FE Specification Break Search Results

Weight	*W150*	*W250*	*W350*	*W450*	*W1*	*W2*
Variable	*Wp*	*Wp*	*HHI*	*Wp*	*Wp*	*Wp*
	HHI	*HHI*	*per60*	*HHI*	*HHI*	-
	-	*perHG*	-	*perHG*	*perSable*	-
	-	-	-	-	*in250*	-
No. of obs	479	517	534	538	542	542

Notes: Unstable parameters associated with variables are given. The number of observations under each weighting scheme is given in the last row.

Table 3. Weight Comparisons

Using *W150*-Sample

Weight	W150	W250	W350	W450	W1	W2
BIC	4.523	4.520	4.511	4.504	4.695	4.514
RMSE	7.807	6.655	6.131	6.229	9.571	7.773

Using *W250*-Sample

Weight	W250	W350	W450	W1	W2
BIC	4.548	4.520	4.499	4.703	4.488
RMSE	5.849	6.640	5.576	6.147	7.684

Using *W350*-Sample

Weight	W350	W450	W1	W2
BIC	4.430	4.428	4.703	4.512
RMSE	14.092	5.624	6.325	7.365

Using *W450*-Sample

Weight	W450	W1	W2
BIC	4.421	4.696	4.509
RMSE	6.737	6.450	7.120

Using Full Sample

Weight	W1	W2
BIC	4.716	4.523
RMSE	7.516	7.521

Table 4. Parameter Estimates

Variable	*W450* Results Param.	SE	*W1* Results Param.	SE
Wp	0.71	0.08	0.23	0.14
DWp	0.10	0.04	0.20	0.06
HHI	7.81	2.32	9.86	2.22
DHHI	-11.74	2.48	-11.44	4.18
perSable	8.19	3.17	7.05	4.03
DperSable	–	–	1.66	4.17
perHG	-13.21	5.91	-7.67	3.02
DperHG	6.68	5.32	–	–
ln250	-6.42	2.98	-11.55	4.06
Dln250	–	–	10.00	4.67
AvgDel	-0.94	0.66	-0.94	0.85
P^{TCWM}	3.45	1.45	10.48	2.08
per60	-2.10	3.27	-3.28	3.53
labor	-0.49	0.23	-0.68	0.28
biom	-0.06	0.04	-0.18	0.07
Hansen J	9.04 (0.34)		6.64 (0.67)	
adj-R^2	0.92		0.90	

Notes DX variables indicate that variable *X* is interacted with the indicator dummy d_τ. Hansen J gives the J-statistic for instrument validity with p-values in parentheses. H_0 of J-statistic is that instruments are valid. adj-R^2 is the adjusted R^2 for each model.

Table 5. Direct and Indirect Effects

| | W450 | | | | W1 | | | |
| | pre-IFQ | | post-IFQ | | pre-IFQ | | post-IFQ | |
Variable	Direct	Indirect	Direct	Indirect	Direct	Indirect	Direct	Indirect
HHI	9.10	18.13	-5.44	-15.11	10.26	2.61	-1.83	-0.96
perSable	9.54	19.01	11.35	31.53	7.34	1.87	10.02	5.27
AvgDel	-1.09	-2.17	-1.30	-3.60	-0.98	-0.25	-1.08	-0.57
P^{TCWM}	4.02	8.01	4.78	13.29	10.91	2.77	12.06	6.34
perHG	-15.38	-30.66	-9.06	-25.16	-7.99	-2.03	-8.83	-4.64
per60	-2.44	-4.87	-2.91	-8.08	-3.42	-0.87	-3.78	-1.99
In250	-7.47	-14.90	-8.90	-24.71	-12.02	-3.06	-1.78	-0.93
Labor	-0.57	-1.15	-0.68	-1.90	-0.71	-0.18	-0.78	-0.41
Biom	-0.07	-0.13	-0.08	-0.22	-0.18	-0.05	-0.20	-0.11

*Notes*: "pre-IFQ" refers to the period 1986-1994. "post-IFQ" refers to the period 1995-2006.

Table 6. Counterfactual Comparison

| Weight | δ_1 | δ_2 | Constant δ | | Constant β | | Constant δ and β | |
			Mean Diff	% Diff	Mean Diff	% Diff	Mean Diff	% Diff
W150	0.59**	0.18**	90.5	44.4	-68.5	-35.6	52.5	24.6
W250	0.58**	0.15**	71.3	34.4	-30.4	-16.3	42.7	25.0
W450	0.72**	0.10**	70.2	34.2	-35.2	-19.3	47.7	22.2
W1	0.23*	0.20**	51.7	24.9	-0.7	-0.0	52.2	25.1
W2	0.54**	0.10**	44.3	21.2	1.8	0.0	44.9	21.6

Notes: "Mean Diff" 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 ($\tau - T$), assuming that δ is constant pre-IFQ implementation ($\hat{p}^1$). Differences in prices are given in ¢/lb. % Diff is the average percentage difference between p_t and and $\hat{p}^1$ over $\tau - T$.
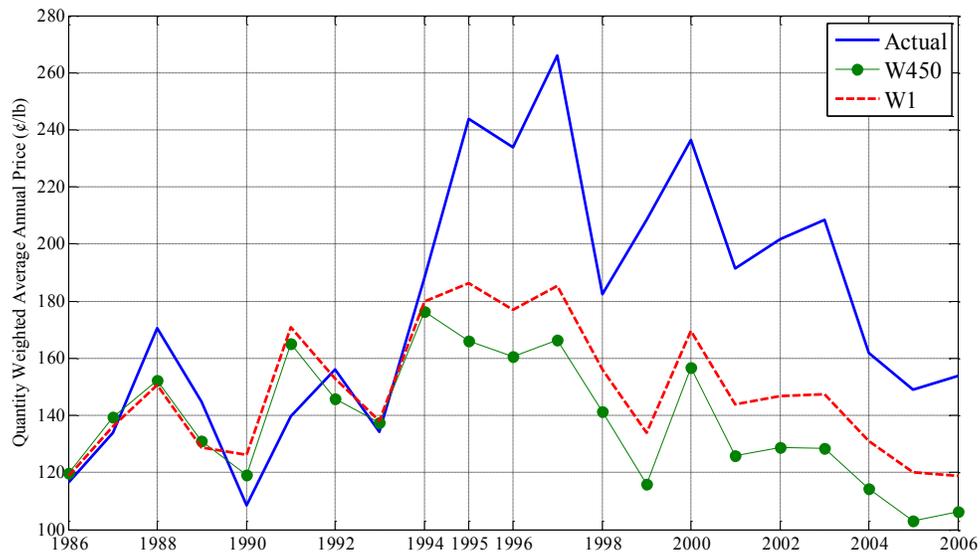
Figures

Figure 1: Sablefish Management Regions and Ports
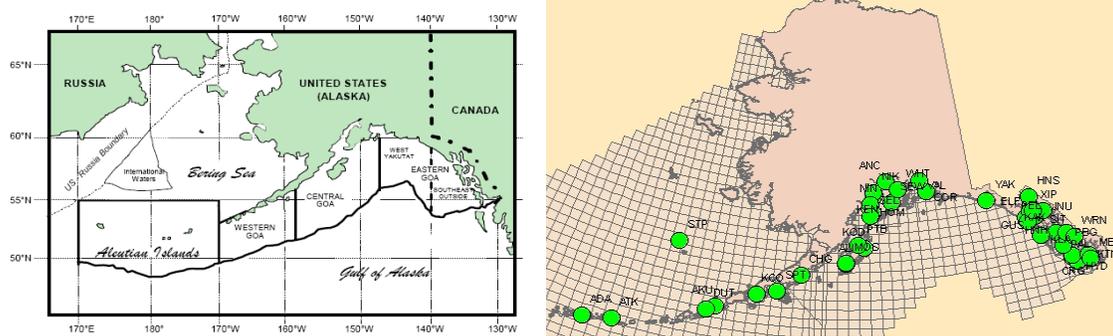
Notes: Left panel figure represents sablefish manamgement regions. Dots on the right-side panel represent locations of ports included in the sample.

Figure 2: Actual versus Constant-δ Predicted Prices

Notes: Prices are quantity-weighted average annual prices. *W450* and *W1* are predicted prices are based on δ remaining constant at pre-IFQ levels for the entire sample.