An Inverse Demand System for New England Groundfish: Welfare Analysis of the Transition to Catch Share Management

Min-Yang Lee[1] and Eric Thunberg[2]

[1]NOAA Fisheries, Northeast Fisheries Science Center, Social Sciences Branch
[2]NOAA Fisheries, Office of Science & Technology, Economics and Social Analysis Division

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Abstract

In 2010, the Northeast groundfish fishery transitioned from an effort-control system (Days-at-Sea) to an output-control system (catch shares). Simultaneously, a large decrease in aggregate catch was imposed in order to achieve biological objectives. This research examines the welfare effects of the transition to catch-share management by combining an inverse demand model for groundfish with a simulation based model of supply. The Generalized Differential Inverse Demand System is estimated for groundfish and imports using monthly data from 1994-2011 using a Generalized Method of Moments estimator. The estimated parameters are combined with simulated landings derived from a counterfactual policy scenario had effort controls been retained instead of the catch share system. The simultaneous management change to catch shares and reduction in aggregate catch reduced consumer welfare by approximately \$11M. A counterfactual policy in which the Days-at-Sea system was adjusted to meet the catch reductions would have reduced consumer welfare by approximately \$37M; this finding is robust to instrument choice in the demand model. Because the 2010 fishing regulations and the counterfactual regulations were designed with the same conservation goals, the difference, approximately \$26M, can be attributed to the change in management institution. Finally, reversion to the Days-at-Sea regulatory structure would reduce consumer welfare by approximately \$25M from the current (2010) levels.

1 Introduction

Cod and other bottom-dwelling fish referred to collectively as "groundfish" have been commercially targeted in the New England waters for over 400 years (Kurlansky, 1998). Compared to other fisheries in New England like lobster (\$365 million annual *ex-vessel* value) and sea scallops (\$400 million), groundfish is relatively modest in size (\$50-100 million). Despite its small size, this fishery continues to be important culturally and politically. The thirteen-species, twenty-stock fishery is managed by the New England Fishery Management Council (NEFMC) under the Northeast Multispecies Fishery Management Plan; hereafter referred to as the Multispecies Plan. Since 1994, the fishery had been managed with an effort control system, Days-at-Sea (DAS), coupled with permanent and seasonal spatial closures, gear restrictions, and minimum sizes designed to achieve annual target catch levels. Exceeding a catch target did not result in a cessation of fishing; instead, annual adjustments were made to the effort control program to meet conservation objectives. This process resulted in a regulatory treadmill in which frequent adjustments to the effort control system were made as fishermen substituted non-regulated inputs for effort and technical change lead to more productive effort. These regulatory changes would affect all fishermen whether or not they fished for the stocks whose catch target had been exceeded.

The Multispecies Plan was amended in 2004 to allow trading of DAS and offer an alternative to DAS management that would allow groups of fishermen to voluntarily form "sectors." Under sector management, members agreed to be bound by a catch quota. In return, sectors were able to request exemptions from certain regulations such as trip limits, access to closed areas, or fishing gear restrictions. More importantly, as long as a sector did not exceed its quota, the sectors quota in the following year would not be reduced even if the fleet as a whole exceeded its catch target. By 2006, only two sectors were in operation, and these sectors represented just a small portion of the groundfish fleet.

In 2006, the Magnuson-Stevens Fisheries Conservation and Management Act (MSFCMA), which establishes Federal authority over fishery management, was reauthorized. In re-emphasizing the requirement to end overfishing, the 2006 reauthorization added a new requirement to establish Annual Catch Limits (ACLs) for all federally managed fisheries along with Accountability Measures (AMs) which prescribe actions to be taken in the event an ACL is exceeded. To meet these new requirements, the Multispecies Plan was amended in 2010. These amendments established a process for setting ACLs, authorized the formation of 17 sectors representing nearly 98% of the aggregate ACLs, and designed an effort control program for "common pool" vessels which did not voluntarily enroll in a sector. This management program was implemented in May of 2010 with large reductions in ACLs needed to end overfishing and rebuild overfished stocks. Vessels which did not join a sector continued to operate in the common pool under the Days-at-Sea system with aggregate stock level ACLs. Input-based regulations made superfluous by the output caps were waived for sector members, but were retained for the fishermen who continued to operate as part of the common pool.

The catch share program has been controversial, producing a coalition of fishing industry groups, public officials from key fishing ports, and Congressional delegations which seek to abandon the program. However, there has been little consideration of an alternative management program which would take the place of catch shares. While a matter of some speculation, reversion to the DAS regulatory system, or some derivative, is one possibility since it had been the basis for managing the groundfish fleet since 1994 and the regulatory structure remains intact for the small portion of the fleet continuing to operate in the common pool.

This research disentangles the impact on consumer welfare associated with the reduction in ACLs from the change in management institutions in order to examine two closely-related research questions. First, what was the welfare impact on consumers of the policy change from DAS-based management to the catch-share system with ACLs? To address this question, we estimate an inverse demand model and compute consumer welfare changes resulting from the 2010 quantities supplied under the catch share program relative to 2009 quantities supplied under the DAS system. Second, what are welfare impacts on consumers of rolling-back the catch-share system in favor of the DAS system? To address this question, we construct a counterfactual model of supply based on regulatory alternatives considered by NEFMC. Using this model, we estimate quantity supplied for 2010, if sectors had not been authorized and all vessels fished under the common pool effort controls. Using these quantities, we can compute consumer welfare changes relative to both the 2009 and 2010 conditions.

The counterfactual regulatory scenario is the DAS regulatory structure with modifications to achieve the conservation goals set for 2010. This regulatory structure mimics the actual regulations that were implemented for common pool participants during 2010. It includes a 50% reduction in allocated days from 2009 levels, a change in the way DAS were counted such that fishing time accrued in 24-hour increments, and changes to possession limits for certain stocks. In all other respects regulations in this counterfactual scenario (trip limits and area closures) are similar to historical regulations. Confronted with a reduction in available fishing days, fishermen may be expected to adjust the timing of fishing effort to optimize returns from fishing. The monthly distribution of fishing effort was determined using a math programming model developed to analyze the biological impacts of the effort control program. This model incorporates temporal heterogeneity in both catch rates and prices to determine the optimal distribution of fishing effort conditional on total allocated days-at-sea.

The landings resulting from these policies are combined with an inverse demand system to compute welfare changes. Estimation of inverse demand models is attractive when the motivating policy analysis concerns quantity changes or when quantities are more likely to be exogenous than price (Huang, 1994). Brown et al.'s (1995) Generalized Differential Inverse Demand system (GDIDS) has frequently been used by many researchers to examine demand for fisheries products; this demand system nests four popular inverse demand systems through the use of just two mixing parameters.

The simultaneous reduction in aggregate catch and management switch to catch shares is found to have reduced consumer welfare by approximately $11M per year. Relative to 2009, the counterfactual policy scenario in which the Days-at-Sea system was adjusted to meet the catch reductions would have reduced consumer welfare by approximately $37M. Because the 2010 fishing regulations and the counterfactual regulations were designed with the same conservation goals, we attribute the difference, approximately $26M, to the change in management institution. Finally, reversion to the Days-at-Sea regulatory structure would reduce consumer welfare by approximately $25M from the current (2010) levels.

2 Demand for Fish

Inverse demand models have frequently been used in modeling demand for fish and other perishables. Use of an inverse, instead of direct, demand model is typically justified on two grounds.

First, the supply of fish is inelastic in the short-run; therefore, quantities, not prices, are predetermined when trade occurs in the market. Second, the fisheries management policy which motivates investigation of demand typically sets quantities, not prices. Anderson (1980) develops some important theoretical properties of inverse demand models. While the Antonelli and Slutsky substitution matrices are generalized inverses, Huang (1994) cautions against inverting either matrix if the other is desired for policy analysis.

Barten and Bettendorf (1989) is an early example of the application of inverse demand systems to demand for fish. Brown et al. (1995) and Park (1996) independently formulated the GDIDS model, which nests the inverse versions of the Rotterdam, Central Bureau of Statistics (CBS), National Bureau of Research (NBR), and Linear-Approximate Almost Ideal Demand System (LA-AIDS) models by using a pair of mixing parameters[1]. This econometric model of demand has been popular in applied fisheries economics: Eales et al. (1997), Park et al. (2004), Lee and Kennedy (2008), Hospital and Pan (2009) utilize the GDIDS to estimate demand for various fish and seafood groups. In these applications, own-quantity flexibilities are typically small, and scale flexibilities are found to be near -1. Because a good is a strong substitute for itself, the demand systems are predisposed to finding complementarity. Alternatives to GDIDS include the Inverse Quadratic AIDS specification (Beach and Holt, 2001; Holt and Bishop, 2002; Hilmer et al., 2010).

We briefly review the derivation of the GDIDS models, parameter restrictions, formulae for flexibilities, and estimation method. The following four equations are the estimating equations for the differential versions of the inverse Rotterdam, AIDS[2], CBS, and NBR demand systems

[1]The Brown et al. (1995) and Park (1996) model is the inverse analogue of Barten's (1993) Generalized Demand System which nests the Rotterdam (Theil, 1965), CBS (Keller and Van Driel, 1985), NBR (Neves, 1987), and LA-AIDS direct demand models (Deaton and Muellbauer, 1980).

[2]Moschini and Vissa (1992) note that while the term "Inverse Linear-Approximate AIDS" has been used to describe an inverse demand system characterized by Equation (2), it is not actually the inverse of the LA-AIDS model. Those authors refer to this as the Linear Inverse Demand System (LIDS). However, we follow the convention in the literature and refer to this as IAIDS.

respectively:

$$w_{it} d\ln v_{it} = \sum_j r_{ij} d\ln q_{jt} + r_i d\ln Q_t \tag{1}$$

$$dw_{it} = \sum_j a_{ij} d\ln q_{jt} + a_i d\ln Q_t \tag{2}$$

$$w_{it} d\ln \frac{p_{it}}{P_t} = \sum_j r_{ij} d\ln q_{jt} + a_i d\ln Q_t \tag{3}$$

$$dw_{it} - w_{it} d\ln Q_t = \sum_j a_{ij} d\ln q_{jt} + r_i d\ln Q_t \tag{4}$$

where $i, j = 1, ...n$ indexes goods, $t = 1, ..., T$ indexes time, w_{it} are expenditure shares, v_{it} is the price normalized by total expenditure at time t, and the lnQ_t and lnP_t terms are quantity and price indices, defined as:

$$\ln Q_t = \sum_{i=1}^{n} \frac{(w_{it} + w_{it-1})}{2} \ln q_{it}$$
$$\ln P_t = \sum_{i=1}^{n} \frac{(w_{it} + w_{it-1})}{2} \ln p_{it}$$

While equations 1 -4 contain different independent variables, the dependent variables are the same. The inverse Rotterdam and CBS models share the same quantity effects (r_{ij}), while the IAIDS and INBR models share the same quantity effects (a_{ij}). The inverse Rotterdam and INBR models share the same scale effects (r_i), while the IADS and ICBS models share the same scale effects (a_i). Barten and Bettendorf (1989) note that the coefficients a and r coefficients are related according to:

$$r_i = a_i - w_i$$

$$r_{ij} = a_{ij} - w_i \delta_{ij} + w_i w_j,$$

where δ_{ij} is the Kronecker delta. Brown et al. (1995) and Park (1996) derive the synthetic nested model by taking a scalar weighted average of all models and summing them, producing:

$$\begin{aligned} w_{it} d\ln v_{it} &= \sum_j \pi_{ij} d\ln q_{jt} + \pi_i d\ln Q_t - \theta_1 w_{it} d\ln Q_t - \theta_2 w_{it} d\ln \frac{q_{it}}{Q_t} \\ &= \sum_j (\pi_{ij} - \theta_2 w_{it} \delta_{ij} + \theta_2 w_{it} w_{jt}) d\ln q_{jt} + (\pi_i - \theta_1 w_{it}) d\ln Q_t \end{aligned} \tag{5}$$

The mixing parameters, θ_1 and θ_2, are bounded between 0 and 1. The parameter restrictions on θ_1 and θ_2 which simplify Equation 5 into one of the four simpler models are listed in Table 1. There are also a set of symmetry, homogeneity, and adding-up restrictions which are required for Equation 5 to be consistent with utility theory:

$$\pi_{ij} = \pi_{ji} \quad \forall i, j \tag{6}$$

$$\sum_i \pi_{ij} = 0 \quad \forall j \tag{7}$$

$$\sum_j \pi_{ij} = 0 \quad \forall i \tag{8}$$

$$\sum_i (\pi_i - \theta_1 w_i) = -1 \tag{9}$$

The compensated cross-quantity flexibilities in the GDIDS are:

$$f_{ij}^c = \frac{\pi_{ij}}{w_i} + \theta_2 w_j,$$

the compensated own-quantity flexibilities are:

$$f_{ii}^c = \frac{\pi_{ii}}{w_i} - \theta_2 + \theta_2 w_i,$$

and the scale flexibilities are:

$$f_i = \frac{\pi_i}{w_i} - \theta_1.$$

The uncompensated quantity flexibilities are derived from the Antonelli equation:

$$f_{ij}^u = f_{ij}^c + w_j f_i$$

Equation 5 can be converted to an estimable form by replacing the differentials with the first- or seasonal-difference operator, adding a constant and an error term:

$$w_{it}\Delta\text{ln}v_{it} = \alpha_i + \sum_j \pi_{ij}\Delta\text{ln}q_{jt} + \pi_i\Delta\text{ln}Q_t - \theta_1 w_{it}\Delta\text{ln}Q_t - \theta_2 w_{it}\Delta\text{ln}\frac{q_{it}}{Q_t} + \varepsilon_{it}. \tag{10}$$

In addition to the constraints in equations (6)-(9), the additional adding-up constraint:

$$\sum_i^n \alpha_i = 0$$

must be imposed. Equation 10 is typically estimated using Seemingly Unrelated Regression (SUR) or Three-Stage Least Squares (3SLS). One equation is usually dropped from the system and the parameter estimates are recovered through the parameter restrictions. When estimated on a time series, residual autocorrelation is frequently encountered; the Feasible GLS procedure described by Parks (1967) was used by both Park et al. (2004) and Hospital and Pan (2009) to allow for valid inference and improve efficiency[3]. However, Greene (2003) notes that this particular FGLS estimator cannot be iterated to produce the maximum likelihood estimator.

Instead of using SUR, a Generalized Method of Moments (GMM) estimator is used to estimate the parameters of Equation 10. This method avoids the iterative GLS procedure required for

[3]An alternative to statistically correcting the model for autocorrelated errors is to respecify the estimating equation. Blanciforti and Green (1983) estimate a dynamic LA-AIDS model by including lagged quantities in the intercept term; however, the authors note that this is an *ad-hoc* adjustment without a basis in utility theory.

inference in the presence of residual autocorrelation. Statistical inference in the presence of autocorrelated errors can be performed using standard errors which are robust to heteroskedasticity and autocorrelation (Newey and West, 1987). Because the system is overidentified due to the parameter restrictions of utility theory, the criterion function-based GMM tests of overidentifying restrictions can be interpreted as general specification tests. Finally, estimation of the full system of equations is not plagued by the singular variance-covariance matrix problem; moment conditions derived from all equations in the system can be used for estimation of all parameters.

However, the GMM method also has disadvantages. It requires an estimation of a weighting matrix, which can be difficult to estimate in practice. While additional moment conditions improve efficiency asymptotically, an excess of moment conditions can lead to biased estimates of the model parameters.

In general, a linear GMM estimator minimizes the function:

$$J(\beta) = [\frac{1}{T}\sum_{t=1}^{T} Z_t \cdot (y_t - X_t\beta)]' W [\frac{1}{T}\sum_{t=1}^{T} Z_t \cdot (y_t - X_t\beta)], \tag{11}$$

where X_t is the $1\text{x}K$ vector of data for observation t, β is a $K\text{x}1$ vector of parameters to be estimated,W is a symmetric positive definite matrix which weights the moment conditions, and e_t is an error term. In addition, Z_t is a $1\text{x}L$ vector of instruments which is uncorrelated with ε_t, correlated with X_t, and may contain elements of X_t. Finally, L must be greater than or equal to K. The minimization typically proceeds iteratively; the initial matrix W is typically set to the identity matrix and consistent estimates of the parameters are estimated. In the next step, a new weighting matrix is constructed using the inverse of the variance matrix of the sample moment conditions; the model is iterated to convergence to produce the optimal GMM estimator. The value of the criterion function can be used as a general specification test (Sargan, 1958; Hansen, 1982). If the model is overidentified, validity of subsets of overidentifying restrictions can be examined using the C- or difference-J statistic; this requires computing two J-statistics, one for the unrestricted model and an additional J statistic in which the suspect overidentifying restrictions are omitted (Eichenbaum et al., 1988).

When the model in equation 10 is estimated on the system of 5 share equations, there are 5 "groups" of moment conditions, one for each equation. Under the assumption that the independent variables are exogenous ($Z = X$), there are 9 moment conditions per equation, for a total of 45 moment conditions. While there are 37 parameters to be estimated, the symmetry, homogeneity, and adding-up restriction imply that there are only 20 independent parameters to be estimated: 10 quantity effects, 4 scale effects, 2 mixing effects, and 4 constant terms.

In the Northeast United States, the National Marine Fisheries Service (NMFS) collects first-sale data for federally managed fish from all entities which buy fish directly from fishing vessels. Much of the fresh and imported fish in the Northeast US is purchased by wholesalers, processing facilities, retailers, or integrated firms. These raw materials are then processed into fillets or steaks, and then distributed through the retail channel. Included in these data are species, market category, quantity, and total value. The dealer report data from 1994-2011 are used to construct a monthly time series of domestic fish prices and quantities. Miscellaneous market categories like cheeks, milt, or livers were excluded from the analysis under the assumption that demand for these categories is weakly separable from demand for whole white fish. Domestic groundfish products were aggregated into three large categories (Table 2): Round 1 (Cod and Haddock), Round 2 (Pollock, White Hake, and Redfish), and Flat (Witch Flounder, Winter Flounder, Yellowtail Flounder, and Plaice)[4]. Monkfish was included as a single species. Quantities and values of imported fish were extracted from a NMFS database which is compiled by the Foreign Trade Division of the U.S. Census Bureau[5]. Most of the round fish are delivered by the vessel with the head on and the gut removed, while the flat fish are typically delivered with the gut intact. A notable exception

[4]While Ocean Pout, Windowpane Flounder, and Halibut are also managed under the NE Multispecies Fishery Management Plan, these were both excluded from the analysis. Ocean Pout and Windowpane Flounder are not directed fisheries and are infrequently landed. Halibut are landed in very limited quantities and are not likely to be substitutes or complements with the rest of the groundfish species.

[5]Available at http://www.st.nmfs.noaa.gov/st1/trade/index.html

is Monkfish, which is valued for both its meat and large liver. The wholesalers and processors which purchase domestic fish in the Northeast are likely to view minimally-processed imports as substitute goods for domestic fish. Therefore, fresh and frozen products of species similar to the domestic fish under examination were aggregated into a single category of imports. Two species were excluded, those containing the large flat fishes (Halibut and Turbot). In addition, the filleted fish and non-specified product forms were excluded as well.

All prices and values are deflated using the Bureau of Labor Statistics Producer Price Index for unprocessed finfish, with the base period set to Jan 2010. In general, expenditure shares, particularly the Round 1 and Imports display major seasonal changes (Figure 1). Domestic flatfish expenditure share has declined through time while imported fish have become more important. Real prices have declined moderately over the time series (Figure 2, left panels). Quantities of flat fish and monkfish have declined slightly since 2005; the other quantities have been fairly constant, though seasonally volatile, through the time series (Figure 2, right panels).

Prior to estimating the demand model, the data are tested for stationarity by using a set of Dickey-Fuller tests. The equation:

$$\Delta y_t = \alpha + \beta y_{t-1} + \epsilon_t \tag{12}$$

is separately estimated for shares, quantities, real prices, and seasonal differences of those variables in this analysis. The augmented Dickey-Fuller test rejects the hypothesis of a unit root for all variables considered, ruling out spurious regression due to unit roots.

3 Simulating Counterfactual Supply and Welfare Measures

The counterfactual policy scenario is our best estimate of the regulatory system which would have been selected by the NEFMC as an alternative to the catch share system. Relative to 2009, available fishing days were reduced by 50%, possession limits were reduced for some stocks of fish, and the manner in which days were counted was changed such that any day or portion of a day was counted as 24 hours. All of these regulatory changes were actually enacted for common pool fishing vessels in 2010. In fact, the majority of other measures affecting fishing gear, area closures, minimum fish sizes, and most possession limits in effect for 2010 were simply carried over from prior years. This means that with the exception of the substantially higher trip limit during 2010 for Georges Bank cod (see Table 3) fishing trips taken during 2008 and 2009 are likely to be representative of trips taken during 2010.

In light of the large reduction in available DAS, fishing vessels are likely to adjust their temporal distribution of fishing. This reallocation was modeled by using a fleet-level math programming model which was initially developed to estimate the biological impacts of the groundfish management alternatives (NEFMC, 2006). This model optimizes operating profits, by allocating effort in spatial and temporal dimensions, given constraints on available DAS, prices, and average catch.

Fishermen engaged in the Northeast groundfish fishery are required to submit a vessel trip report (VTR) for every trip. Trips which occurred during 2008 and 2009 are the basis for simulating supply under the counterfactual policy. VTR data includes information about fishing gear, area fished, crew, weight of all species retained for sale, and estimated weight of all species discarded, the port of landing, the date sailed, and date landed. Date sailed and date landed provide an estimate of the elapsed time or days absent between the start and end of a fishing trip. Of the required variables, only weight by species, date sailed, and date landed for the 2008 and 2009 fishing years (May 1 to April 30) were needed for each trip to estimate counterfactual landings.

Trip data, stratified by month to match the inverse demand model, forms the population from which counterfactual supply is simulated. Two adjustments were made to the trip data to model the counterfactual policy. First, the estimated number of days absent for each trip was rounded up to the nearest whole 24-hour day. For example, an 8-hour trip was converted to 24-hours and a 25-hour trip was converted to 48 hours. Second, if a 2008/2009 trip retained any species or stock with a zero possession limit in 2010, the pounds of fish were set equal to zero for that species. After adjusting for prohibited species, a trip was included only if it retained at least one of the species aggregates modeled in the inverse demand system.

The counterfactual supply of each aggregate plus monkfish was simulated by drawing trips, with replacement, from the adjusted population of groundfish trips until the monthly DAS used was equal to the optimal temporal distribution of DAS. Monthly quantities were aggregated from the trip-level landings. Approximately 75% of monkfish are landed on trips where no groundfish were landed. Monkfish supplied outside of the groundfish fishery were deducted from monkfish landed on groundfish trips and held constant at 2009 levels. Import quantities are also assumed to be fixed.

Variability and uncertainty in our welfare measures were included in the simulation using the Krinsky and Robb (1986) method. Parameters values are drawn from a multivariate normal distribution with mean and variance-covariance matrix taken from the econometric model; each random draw is paired with a simulated fishing year. The simulation was implemented in EXCEL with the @RISK add-in. A total of 500 fishing years were simulated.

Kim (1997) describes the appropriate welfare measures for quantity space. Given a well-behaved utility function $U = F(\mathbf{X})$ and the corresponding indirect utility function $V(\hat{\mathbf{P}})$, where $\hat{\mathbf{P}} = \{\hat{p}_1, \hat{p}_2, \dots \hat{p}_n\}$ and $\mathbf{X} = \{x_1, x_2, \dots x_n\}$ are vectors of (normalized) prices and quantities respectively, the dual expenditure and distance functions can be defined as:

$$E(\hat{\mathbf{P}}, u) = \min_{\mathbf{X}} \{\hat{\mathbf{P}}'\mathbf{X} : D(u, \mathbf{X}) \geq 1\} \tag{13}$$

and

$$D(u, \mathbf{X}) = \min_{\hat{\mathbf{P}}} \{\hat{\mathbf{P}}'\mathbf{X} : E(\hat{\mathbf{P}}, u) \geq 1\} \tag{14}$$

Shephard's lemma can be applied to the distance function to produce the normalized compensated inverse demand system:

$$P_i = \frac{\partial D(u, \mathbf{X})}{\partial x_i} = a_i(u, \mathbf{X}) \tag{15}$$

The corresponding set of normalized uncompensated inverse demand equations are:

$$b_i(\mathbf{X}) = a_i(F(\mathbf{X}), \mathbf{X}) \tag{16}$$

The Compensating and Equivalent Variation welfare measures associated with changes in quantities are given by:

$$CV = D(u^0, \mathbf{X}^1) - D(u^0, \mathbf{X}^0) \tag{17}$$

$$EV = D(u^1, \mathbf{X}^1) - D(u^1, \mathbf{X}^0). \tag{18}$$

For a change in quantity of single arbitrary good k , equations 17 and 18 can be written as:

$$CV = \int_{x_k^1}^{x_k^0} a_k(u^0, \mathbf{X}) dx_k$$
$$EV = \int_{x_k^0}^{x_k^1} a_k(u^1, \mathbf{X}) dx_k.$$

When considering change in multiple quantities, equations 17 and 18 can be expressed as:

$$CV = -\int_L \mathbf{a}(u^0, \mathbf{X}) d\mathbf{X}$$
$$EV = \int_L \mathbf{a}(u^1, \mathbf{X}) d\mathbf{X},$$

where $\mathbf{a}(u, \mathbf{X})$ is the system of inverse demand equations and L is an arbitrary path of integration with initial point $\mathbf{X}^0$ and ending point $\mathbf{X}^1$.

The GDIDS model in equation 5 is not derived from a distance or expenditure function approach and does not have a closed form equation for the associated expenditure function. However, the appropriate welfare measures can be approximated by numerically integrating under the inverse demand curves. A "second-order" approximation is frequently used; this method assumes that the inverse demand curve is linear across the quantity change and the area under the inverse demand curve can be approximated using a trapezoid (Park et al., 2004). This may not be appropriate for large changes in quantities. Therefore, welfare measures are calculated by decomposing the large quantity changes into smaller quantity changes, over which the "second-order" approximation is more likely to hold.

The CV computation is straightforward and uses the compensated flexibilities. However, because the GDIDS is not derived from a closed form expenditure or distance function, computation of EV requires use of the uncompensated demand curve to compute prices at the final set of quantities. The EV measure will consistently rank 2 or more policy alternatives and is, itself, an indirect utility function (Mas-Colell et al., 1995). The EV and CV measures are both invariant to the path of integration. However, the traditional consumer surplus measures and prices along the uncompensated demand curve are not path independent. The uncompensated demand curve is used to construct the "initial" prices for the EV measure; this implies that EV measure will depend on the path taken along the uncompensated demand curves.

4 Results

The demand model is estimated using three specifications. The first specification ("Exogenous") is estimated under the assumption that independent variables are exogenous and therefore can serve as instruments for themselves. The second specification ("IV") is estimated under the assumption that the independent variables are endogenous and first lags of the seasonal differences are appropriate instruments. Finally, the third specification ("Large") is estimated under the assumptions that both the independent variables and first lags are uncorrelated with the error terms. Researchers have included monthly dummy variables in the estimation, to account for seasonality in supply or demand which occurs on a monthly time scale (See Eales et al. (1997) and Hospital and Pan (2009) for examples). Incorporating monthly dummy variables would greatly increase the number of moment conditions; instead, the demand model is estimated using seasonal differences.

Table 4 contains parameter estimates for three estimated GDIDS models. Standard errors presented are robust to heteroskedasticity and autocorrelation and calculated using the Newey and West (1987) method, setting the bandwidth equal to 4. Also included in Table 5 are the J-and C-statistics. The J-statistic is the optimized value of the GMM criterion function. Under the null hypothesis of correct specification of the moment conditions, the J-statistic is distributed χ^2 with degrees of freedom equal to the number of overidentifying restrictions. The J-statistics in Table 5 can be interpreted as evidence that all three models are properly specified. However, the large p-value for the "Large" model may be symptomatic of too many moment conditions; this specification test is known to have low power when the number of instruments is large (Roodman, 2009). The C-statistic is the difference in J-statistics corresponding to alternative instrument sets and is used to test for appropriateness of a subset of excluded instruments. Under the null hypothesis of correct specification of the moment conditions, the C-statistic is distributed χ^2 with degrees of freedom equal to the number of overidentifying restrictions in the subset of excluded instruments. Similarly, the C-statistics do not clearly prefer the "Exogenous" model to the "IV" model. The GDIDS model can be simplified to alternative models depending on the mixing parameters, θ_1 and θ_2. The Wald test statistics corresponding to the nested models in Table 6 support the generalized model, with possible exception of the IROT and ICBS nested models estimated using the IV specification. This finding is due to an imprecisely estimated θ_1 parameter in this specification. The GMM criterion-based statistics do not strongly advocate for either of the three econometric specifications. Excess moment conditions in the "Large" model may lead to biased estimates of the model parameters. We opt for estimates which are less likely to be biased, but have less precision, and present flexibilities and and conduct policy analysis using the results from the "Exogenous" and "IV" models under the most general version of the GDIDS specification.

Tables 7 and 8 contain the compensated own-quantity, cross-quantity, and scale flexibilities evaluated at the means of the data for the “Exogenous” and “IV’ models. The scale effects describe the price response to a proportional shift in all quantities. The estimated scale flexibilities in both models are very similar in magnitude and degree of precision; the Round 1 and Monkfish scale flexibilities are close to -1, while the Import flexibility is much smaller in magnitude, while the Round 2 and Flat flexibilities are fairly large in magnitude. The own-quantity flexibilities are all negative and relatively small in magnitude; this is similar to findings by previous researchers. In addition, some goods are found to be complementary, a finding which is also prevalent in the literature. These findings are likely to be related to the parameter restrictions required under utility theory; because all goods are relatively strong substitutes for themselves, the demand system is predisposed to finding complementarity.

Tables 9 and 10 contain the uncompensated own-quantity and cross-quantity flexibilities. The uncompensated flexibilities describe the slope of the demand curve along which the consumer has not been compensated with additional income. With a single exception, all of the uncompensated flexibilities are negative. The Antonelli matrix is confirmed to be negative semi-definite for both the “Exogenous” and “IV” specifications; all eigenvalues of the Antonelli matrix are either zero or within machine precision of zero.

The counterfactual model of supply agrees well with the historical trends in landings, although it does produce lower quantities due to the dramatic reduction in available DAS (Figure 3). For example, Round 1 landings increase from May to June in both 2009 and the counterfactual model, declining through October and then increase steadily through the fishing year. In 2010, Round 1 landings remained relatively high in May and June, decreased sharply in July and then roughly followed the 2009 pattern for the rest of the fishing year. The counterfactual model of Round 2, Flat and Monk also follows the 2009 patterns closely. While the general patterns of landings are similar the nominal changes between the three landings scenarios are often very large: the counterfactual DAS model frequently produces decreases of 50% or greater relative to both 2009 and 2010 in many months. The exception is for Monkfish; this occurs because the only a small amount of Monkfish are caught jointly with the other species.

Figure 4 plots compensating variation for various policy scenarios and econometric models. The comparison of 2009 to 2010 landings is evaluated by fixing landings at the 2010 levels and computing compensating variation using parameters from the exogenous demand system. The mean compensating variation for the actual policy change from 2009 to 2010 landings is approximately \$11M, implying that consumers of groundfish would require \$11M in compensation in order to restore 2009 utility levels, given 2010 landings. The variation associated with this estimate is low because only parameter variability is captured since supplies are fixed at their observed levels. The second column of Figure 4 contains the CV estimate for the Days-at-Sea counterfactual policy using the simulated landings and parameters from the exogenous demand system. In this scenario, consumer welfare losses are approximately \$37M. The third column of Figure 4 contains the CV estimate for the Days-at-Sea counterfactual policy using the simulated landings and parameters from the IV specification of the demand system. Welfare losses are similar; however,there is greater dispersion in the estimates of CV. The final column of Figure 4 contains the CV estimate associated with the transition from 2010 actual landings to the Days-at-Sea counterfactual policy using the simulated landings and parameters from the exogenous specification of the demand system. Mean welfare losses for consumers are approximately \$25M.

Figure 5 contains analogous plots of equivalent variation for various policy scenarios and econometric models. The EV measures are less precise than the CV estimates. This is caused by the approximation method used. Because the GDIDS does not have a closed form expenditure or distance function, the uncompensated demand curves are used to “move” the consumer from initial utility to final utility level.

5 Discussion and Conclusions

In this research, a model of supply is combined with a model of demand to examine the effects of hypothetical changes in policy on groundfish consumers in the Northeast United States. The GDIDS model has been frequently used in applied research, even though the exact estimation method used herein has not. The estimated parameters are similar to estimates found in the literature of other aggregates of fish. The relatively large scale flexibilities for the species aggregates indicate that these goods are, in a broad sense, substitutes for each other. The scale flexibility for Imports is substantially smaller in magnitude than the rest of the estimated scale flexibilities suggesting that imports do not as readily substitute for fresh fish. However, imported unprocessed fish are often sourced from Canada, Iceland, or Norway. It is likely that buyers and sellers are contracting for future delivery and are operating in a slightly different market from the fresh fish market. If this is the case, a richer model of imports may be warranted.

When computing welfare measures related to the policy changes, imports are assumed to remain constant relative to the baseline year. Because a large reduction in fishing effort and landings is embedded in the counterfactual model, this assumption seems doubtful from a theoretical standpoint. Indeed, prior research (Jin et al., 2006) found that processors do substitute imports for domestically available fish. Processors may be expected to anticipate lower levels of supply and contract for delivery of more imported fish as substitutes leading to lower prices for all fish. By holding import quantities constant, the prices of domestic fish embedded in the counterfactual welfare measures are likely to be higher than they would be if imported quantities were allowed to change. This model shortcoming means that the counterfactual scenarios are likely to overestimate losses in CV and EV.

Meeting the statutory requirement in the MSFCMA to end overfishing and manage fisheries using ACLs is difficult. Catch-shares, and other well-designed property rights, can be a way to meet those requirements. This institutional change in New England has disadvantaged some resource users, producing vocal opposition to the catch share program. This research finds that the transition to catch shares in the groundfish fishery reduced consumer welfare by approximately \$11M. Had the DAS regulatory system been retained, the aggregate quantity of groundfish supplied would have been substantially lower and would have reduced consumer welfare by approximately \$37M. While some loss in consumer welfare was unavoidable, the catch share program mitigated these losses substantially.

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6 Tables

Parameter	IROT	IAIDS	ICBS	INBR
θ_1	0	1	1	0
θ_2	0	1	0	1

Table 1: Parameter restrictions in the GDIDS result in simplification to four alternative models.

Species	2010 Landings ('000s of pounds)	2010 Value ($000s)	Average price	Aggregate Grouping
Cod	20,153	12,467	$1.62	Round1
Haddock	15,436	16,683	0.93	Round1
White Hake	3,515	3,609	0.97	Round2
Pollock	7,370	10,629	0.69	Round2
Redfish	1,826	4,196	0.44	Round2
Monkfish	14,017	8,281	1.69	Monkfish
Winter Flounder	5,256	3,450	1.52	Flat
Witch Flounder	2,678	1,470	1.82	Flat
Yellowtail Flounder	2,838	2,991	0.95	Flat
American Plaice	3,215	2,958	1.09	Flat
Windowpane Flounder	46	98	0.47	-
Atlantic Halibut	192	36	5.27	-
Ocean Pout	< 1	< 1	0.38	-
Import	39,315	48,487	0.81	Import

Table 2: Groundfish landings, prices, and aggregation levels used in this analysis. Economic values normalized to Jan 2010 real dollars.

Species	2008-2009	2010
Georges Bank cod	1,000 lbs/ day 10,000 lbs/ trip	2,000 lbs/ day 20,000 lbs/trip
Cape Cod, Gulf of Maine yellowtail flounder	250 lbs/day 1,000 lbs/trip	250 lbs/day 1,5000 lbs/trip
Southern New England, Mid-Atlantic yellowtail flounder	250 lbs/day 1000 lbs/trip	250 lbs/day 1,500 lbs/trip
Southern New England, Mid-Atlantic winter flounder, ocean pout & windowpane flounder	no limit	0 lbs

Table 3: Summary of possession limits in 2008/2009 and 2010.

Coefficient	Exogenous	IV	Large
α_{r1}	0.00498***	0.00115	0.00310***
	(0.00168)	(0.00221)	(0.000939)
π_{r1r1}	-0.0227*	0.0116	-0.0372***
	(0.0121)	(0.0167)	(0.00692)
π_{r1r2}	0.0168***	0.0150***	0.0146***
	(0.00232)	(0.00404)	(0.00160)
π_{r1mk}	6.56e-05	-0.0118	0.000773
	(0.00405)	(0.00867)	(0.00247)
π_{r1fl}	0.0257***	0.0122	0.0372***
	(0.00498)	(0.00918)	(0.00297)
π_{r1}	-0.135***	-0.0719	-0.203***
	(0.0285)	(0.101)	(0.0160)
θ_1	0.508***	0.739*	0.206***
	(0.125)	(0.432)	(0.0679)
θ_2	0.190***	0.228**	0.0743**
	(0.0613)	(0.103)	(0.0336)
α_{r2}	7.78e-05	0.000799	-8.49e-05
	(0.00107)	(0.00124)	(0.000637)
π_{r2r2}	-0.0268***	-0.0232***	-0.0254***
	(0.00459)	(0.00795)	(0.00274)
π_{r2mk}	0.00525**	0.00368	0.00907***
	(0.00225)	(0.00557)	(0.00135)
π_{r2fl}	-0.000262	0.00858	-0.00168
	(0.00268)	(0.00582)	(0.00160)
π_{r2}	-0.0672***	-0.0546*	-0.0853***
	(0.0102)	(0.0330)	(0.00559)
α_{r3}	0.00340	0.00520	0.00396***
	(0.00294)	(0.00392)	(0.00148)
π_{mkmk}	-0.00756	-0.00665	-0.0235***
	(0.0110)	(0.0224)	(0.00647)
π_{mkfl}	0.0125***	0.0142	0.0166***
	(0.00474)	(0.00898)	(0.00258)
π_{mk}	-0.0732***	-0.0420	-0.124***
	(0.0215)	(0.0828)	(0.0138)
α_{r4}	-0.00663***	-0.00778***	-0.00639***
	(0.00178)	(0.00246)	(0.00106)
π_{flfl}	-0.0443***	-0.0462***	-0.0698***
	(0.0119)	(0.0175)	(0.00659)
π_{fl}	-0.162***	-0.107	-0.233***
	(0.0289)	(0.0907)	(0.0149)
J	24.5	26.2	35.4
C	9.9	9.1	
*** p<0.01, ** p<0.05, * p<0.10			

Table 4: Parameter estimates for the Generalized Differential Inverse Demand system. Standard errors below in parentheses, n=194.

	Exogenous	IV	Large
J-statistic	24.5	26.2	35.4
DF	25	25	60
p-value	0.49	0.39	0.995
C-statistic (valid moments)	9.9	9.1	-
DF	35	35	
p-value	0.99	0.99	

Table 5: Criterion function based specification diagnostics of the GDIDS do not strongly prefer any of the three specifications.

	Exogenous	IV	Large
INBR	365	70.3	1090
$\theta_1 = 0, \theta_2 = 1$	(<0.0001)	(<0.0001)	<0.0001)
IROT	17.6	6.24	10
$\theta_1 = 0, \theta_2 = 0$	(0.0001)	(0.044)	(0.007)
IAIDS	192	57.8	759
$\theta_1 = 1, \theta_2 = 1$	(<0.0001)	(<0.0001)	(<0.0001)
ICBS	56.6	6.39	214
$\theta_1 = 1, \theta_2 = 0$	(<0.0001)	(0.041)	(<0.0001)

Table 6: Wald test statistic values (p-values below in parentheses) for the 4 models nested in the GDIDS. Test statistics are distributed χ^2_2 under the null hypothesis that the demand system is one of the nested models.

	Round 1	Round 2	Monkfish	Flat	Import	Scale
Round 1	-0.250	0.0889	0.0357	0.159	-0.0337	-1.116
	(0.0187)	(0.00866)	(0.0157)	(0.0147)	(0.0198)	(0.0386)
Round 2	0.279	-0.555	0.110	0.0396	0.127	-1.457
	(0.0272)	(0.0363)	(0.0296)	(0.0372)	(0.0313)	(0.0438)
Monk	0.0426	0.0416	-0.195	0.111	0.000334	-0.901
	(0.0187)	(0.0113)	(0.0372)	(0.0214)	(0.0269)	(0.0577)
Flat	0.155	0.0123	0.0904	-0.341	0.0832	-1.219
	(0.0144)	(0.0116)	(0.0175)	(0.0257)	(0.0180)	(0.0443)
Import	-0.0256	0.0308	0.000213	0.0649	-0.0703	-0.693
	(0.0150)	(0.00757)	(0.0171)	(0.0140)	(0.0147)	(0.0427)

Table 7: Compensated Price flexibilities and Scale flexibility (standard errors below) for the "Exogenous" model, evaluated at mean quantities.

	Round 1	Round 2	Monkfish	Flat	Import	Scale
Round 1	-0.125	0.0836	-0.0106	0.107	-0.0547	-1.063
	(0.0305)	(0.0187)	(0.0366)	(0.0316)	(0.0307)	(0.0468)
Round 2	0.262	-0.539	0.0944	0.173	0.00922	-1.510
	(0.0585)	(0.0768)	(0.0709)	(0.0867)	(0.0683)	(0.0762)
Monk	-0.0127	0.0359	-0.221	0.128	0.0697	-0.964
	(0.0437)	(0.0270)	(0.0834)	(0.0475)	(0.0582)	(0.0788)
Flat	0.104	0.0538	0.105	-0.379	0.116	-1.210
	(0.0308)	(0.0269)	(0.0388)	(0.0596)	(0.0360)	(0.0624)
Import	-0.0415	0.00223	0.0444	0.0901	-0.0952	-0.688
	(0.0233)	(0.0165)	(0.0371)	(0.0281)	(0.0384)	(0.0444)

Table 8: Compensated Price flexibilities and Scale flexibility (standard errors below) for the "IV" model.

	Round 1	Round 2	Monkfish	Flat	Import
Round 1	-0.498	0.00982	-0.172	-0.0956	-0.360
	(0.0195)	(0.00953)	(0.0169)	(0.0175)	(0.0234)
Round 2	-0.0449	-0.659	-0.162	-0.293	-0.299
	(0.0278)	(0.0366)	(0.0310)	(0.0384)	(0.0340)
Monk	-0.158	-0.0222	-0.363	-0.0949	-0.263
	(0.0201)	(0.0125)	(0.0452)	(0.0210)	(0.0221)
Flat	-0.116	-0.0741	-0.137	-0.619	-0.273
	(0.0108)	(0.0124)	(0.0210)	(0.0285)	(0.0230)
Import	-0.180	-0.0183	-0.129	-0.0931	-0.287
	(0.0159)	(0.00907)	(0.0225)	(0.0137)	(0.0349)

Table 9: Uncompensated Price flexibilities (standard errors below) for the "Exogenous" model.

	Round 1	Round 2	Monkfish	Flat	Import
Round 1	-0.361	0.00835	-0.209	-0.135	-0.365
	(0.0289)	(0.0201)	(0.0413)	(0.0273)	(0.0350)
Round 2	-0.0732	-0.646	-0.187	-0.171	-0.432
	(0.0552)	(0.0787)	(0.0767)	(0.0835)	(0.0710)
Monk	-0.227	-0.0324	-0.401	-0.0915	-0.212
	(0.0414)	(0.0289)	(0.0936)	(0.0454)	(0.0493)
Flat	-0.165	-0.0319	-0.120	-0.654	-0.238
	(0.0339)	(0.0293)	(0.0443)	(0.0559)	(0.0381)
Import	-0.195	-0.0465	-0.0839	-0.0668	-0.257
	(0.0232)	(0.0176)	(0.0431)	(0.0287)	(0.0527)

Table 10: Uncompensated Price flexibilities (standard errors below) for the "IV" model.

7 Figures

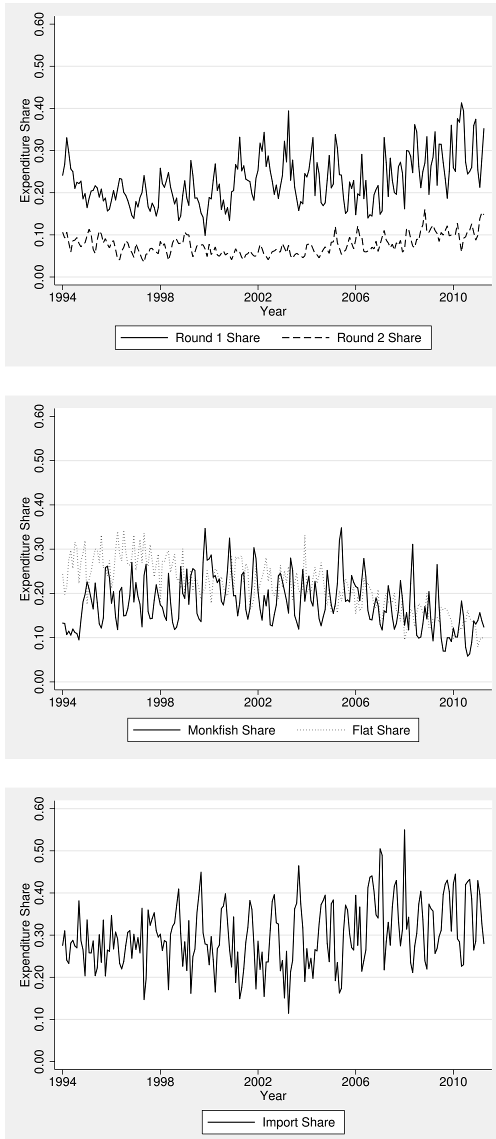
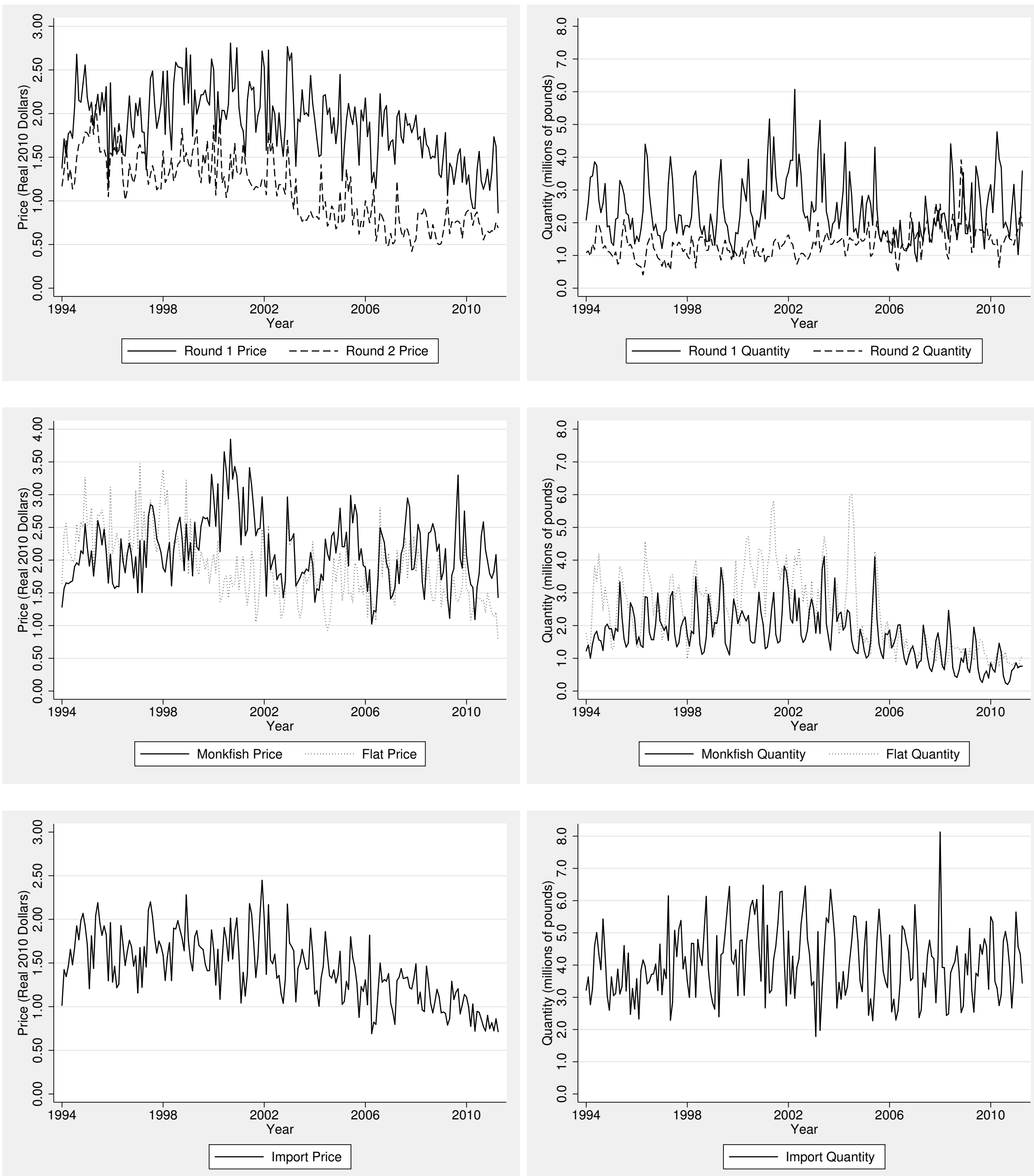
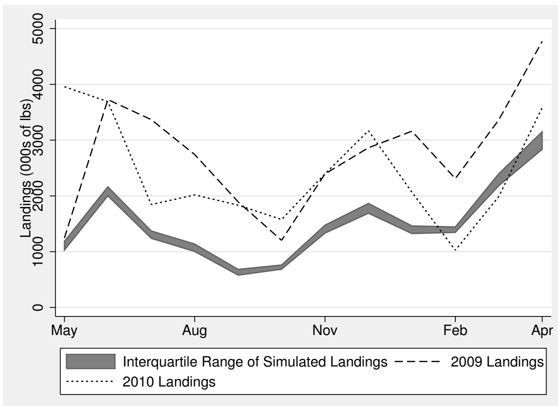


Figure 1: Expenditure Shares for Domestic and Imported Fish.

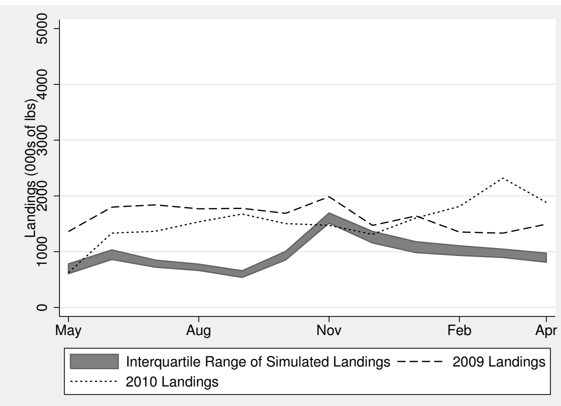


(a) Real Prices (b) Quantities

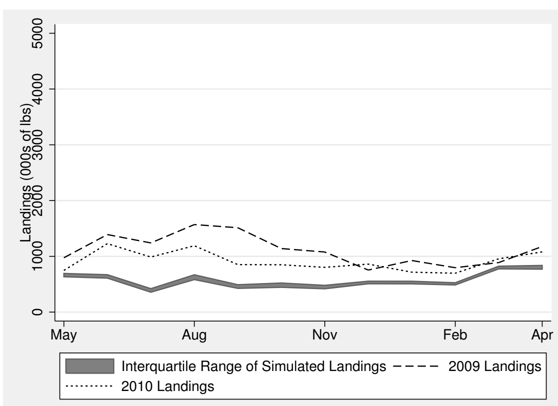
Figure 2: Timeseries of Real Prices (a) and Quantities (b) for the five aggregate fish groupings.



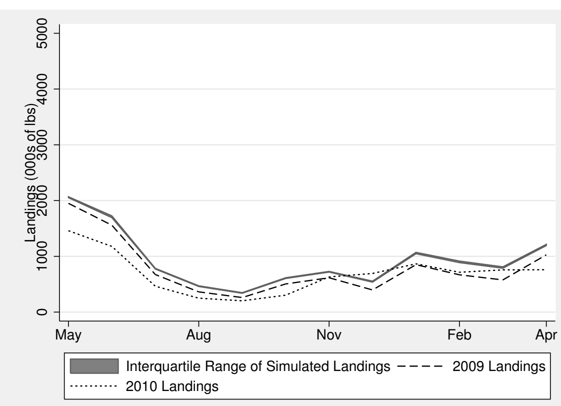
(a) Round 1



(b) Round 2



(c) Flat



(d) Monkfish

Figure 3: 25^{th} to 75^{th} percentiles of the countefactual landings along with actual 2009 and 2010 landings. In general, the counterfactual set of landings and the 2009 landings have a similar temporal distribution, although the 2009 landings are typically much larger.

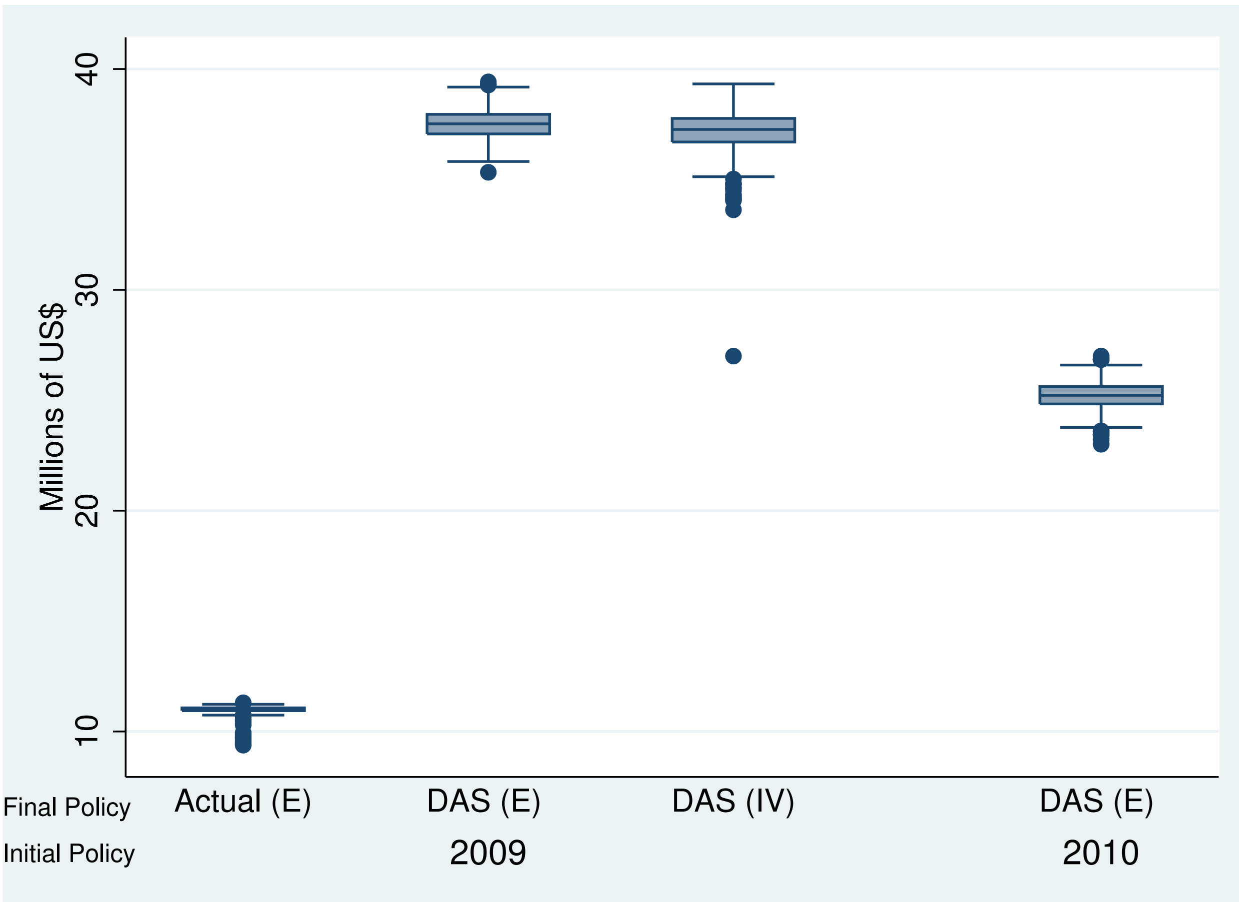


Figure 4: Compensating Variation (CV) for the actual change from 2009 to 2010 quantities is approximately \$11M. CV for the change from 2009 to the DAS counterfactual is approximately \$37M; the "IV" demand model produces less precise estimates than the "Exogenous" demand model. CV for the change from 2010 to the DAS counterfactual is approximately \$25M.

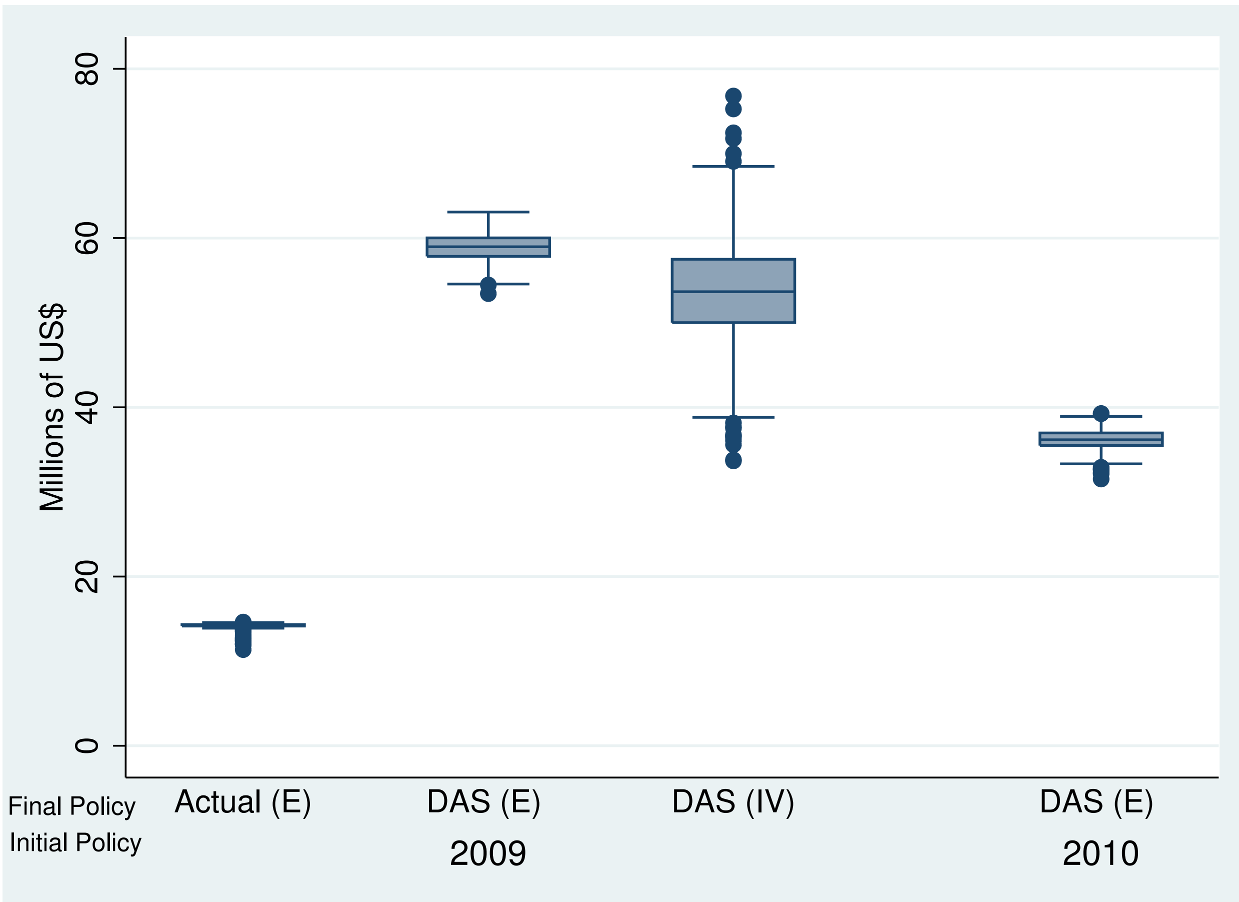


Figure 5: Compensating Variation (CV) for the actual change from 2009 to 2010 quantities is approximately $14M. EV for the change from 2009 to the DAS counterfactual is approximately $58M using parameters estimated from "Exogenous" demand model and approximately $54M when using parameters estimated from the "IV" demand model. EV for the change from 2010 to the DAS counterfactual is approximately $36M.