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The Day-to-day Supply Responses of a Limited-entry Mixed Fishery

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ABSTRACT

Small-scale fishers' short-run supply decisions are understudied, often because of data limitations. We utilize a unique dataset of daily catches and prices from a mixed-species trawl fishery in Taiwan, characterized by targeting decisions made before prices are formed. To investigate the effect of expected prices on fishers' supply decisions, we formulate a vector error correction model in a seemingly unrelated regression system of 11 fish species. We find the price-elastic short-run supply for several species: the maximum daily price elasticity of supply (PES) ranges from 0.4–1.1 and is statistically significant for all but one species. The long-run PES (approx. weekly) is > 1 for eight species. In contrast, elasticity with respect to wave height is weak (the median short-run elasticity -0.4). These findings are unexpected for trawl fisheries believed to have low selectivity. Our results highlight the potential that auction markets have to incentivize fishing that emphasizes quality over quantity.

Keywords: Mixed-fisheries, small-scale fisheries, price expectations, supply responses, error correction model, seemingly unrelated regression

JEL codes: Q210, Q220

1 Introduction

Fishermen make repeated decisions with respect to going fishing or not, which species to target, and where to catch them. These decisions are influenced by factors including regulation, technology, weather, expectations about prices, costs, and fish abundance (Wilen et al., 2002). Some of these factors are relatively latent, with little or no changes in the short-run, whereas others are subject to rapid changes, such as in weather and prices. Compared to long-term fleet dynamics, fishers' short-term decisions, e.g., day-to-day decisions, have not received sufficient attention either from research scholars or fisheries authorities (Rijnsdorp et al., 2011). Understanding the short-term dynamics is important for predicting and designing efficient regulatory programs (Wilen et al., 2002; Salas and Gaertner, 2004).

The focus of this paper is on the effect of short-term price variations on fishers' supply decisions. The importance of price in the fisher's decision is evident. Fisheries models typically assume fishers to be profit maximizers (Salas et al., 2004) responding to economic incentives such as price (Dupont, 1993). Survey interviews of fishers have also confirmed this; for instance, Bastardie et al. (2013) found that fish prices and weather are two key factors that Danish fishers consider when deciding whether to go fishing, and the potential for sizable catches determines their choices of fishing grounds and target species. Studies on the supply elasticity of fishers, however, do not fully corroborate this expectation. The short-run supply of fish and fish products is typically found to be price inelastic (Jensen, 2002). Frequently, such evidence is drawn upon from regulated fisheries, or fisheries with limited numbers of species. Moreover, it is common to assume that fishers form rational price expectations (Muth, 1961), that is, they do not make systematic forecast errors. Would, then, the conclusion differ for fisheries that are subject to open or semi-open access with active market transactions, and also if we allow for alternative assumptions about fishers' price expectations?

We investigate these questions using day-to-day catch statistics from coastal mixed fisheries in Taiwan. Coastal fisheries in East Asia share several distinct features: they are often small in scale and associated with vibrant domestic fresh fish markets characterized by market participants exhibitinging an intrinsic preference for fresh catches (Yamamoto, 1995). Fresh fish caught on shorter trips receive a price premium (Sogn-Grundvåg et al., 2013; Lee, 2014). Consumers of East Asian ethnicity perceive high utility from consuming fresh or live fish (Thapa et al., 2015; Dey et al., 2008).

Such consumer preferences could shape fishers' harvesting practices. To secure the price premium, coastal fleets supplying local markets often only use ice to chill their catches (Abe, 2017). This distinguishes them from many other fleets where catches are typically frozen on board and/or serve international markets. Because fresh or chilled fish is perishable, fishers are encouraged to make shorter fishing trips.

A rich mix of species is another defining feature of the coastal fisheries in East Asia and elsewhere in the subtropical and tropical coastal seas. Studies based on mixed fisheries show that shifting target species is an important risk mitigation strategy (Kasperski and Holland, 2013), more so for small-scale fishers (Salas et al., 2004). The third feature is the relatively slack fisheries management. Coastal fisheries in the region, China in particular, are principally controlled by licenses (e.g., Shen and Heino, 2014). License control creates a semi-open access regime in which fishers have much more freedom to respond to price signals and exploit the stocks at their disposal, compared to quota-regulated fisheries. The combination of vibrant fish markets, a rich selection of species, and rudimentary fisheries management (i.e., limited entry) makes East Asia an interesting region to study fishers' price responsiveness.

Attempts to study fishers' short-term decisions in non-regulated fisheries are often hampered by a lack of data. We have been able to obtain a unique data set of daily catch and price statistics from a coastal trawl fishery in southwestern Taiwan. The data set covers an extensive period of time (2001–2015) and has daily temporal resolution (On-line supplement S1). The data have been obtained from public sources as well as through the authors' visits to the fishing market in question. Existing studies on the price elasticity of supply typically rely on aggregated cross-sectional data that often have only annual resolution, and come from regulated fisheries or from consumer markets (Diop and Kazmierczak Jr, 1996; Salvanes and Squires, 1995; Pascoe et al., 2011). Our species-specific daily data from production markets offer us unique possibilities to study the short-run supply responses of semi open-access fisheries.

2 Literature review

The important feature of coastal fisheries serving fresh food markets is that there exists a natural decision lag between the time a harvest decision is made and the time the prices are realized. Because prices are volatile on a daily scale, fishers act on the expected prices (Griliches and Mairesse, 1995). It is not common, however, to discuss fishers' price expectations in the fisheries economic literature. Exceptions include Dupont (1993) and Kristofersson and Rickertsen (2009) who used the expected prices predicted by an ARIMA price model. By contrast, decisions with lags have been commonly featured in the agronomic literature, stemming from the seminal work of Nerlove (1958). In these studies, farmers encountering similar price delays or decision lags are price takers and possess rational or quasi-rational expectations (Nerlove and Bessler, 2001). Typically, expected prices are taken from futures prices (instrumented or uninstrumented), lagged prices, or predicted prices from a univariate time series (Roberts and Schlenker, 2013). While these studies provide the theoretical and empirical basis for our study, the difference between farming and fishing is evident. Most obviously, the supply of agricultural products typically deals with an annual lag, whereas for the fresh fish market, the delay is short, being about one day. Moreover, multi-output can be important for mixed fisheries production, but is less of an issue in agricultural production. Pascoe et al. (2007) argued that in mixed fisheries, the production of one output does not reduce the supply of the input for the production of other outputs, a technology termed "mostly joint but not purely joint". Our model accounts for potential multiple outputs by estimating all species-specific catch equations jointly, using the systems of equations approach that allows for correlation among the error terms across the equations.

The effect of output price on output quantity can emerge from fisheries studies on economic productivity or technical efficiency (Squires, 1987; Chiang et al., 2004; Tingley et al., 2005; Asche et al., 2009). Implicitly or explicitly, these studies assume rational price expectations, that is, no systematic error in price forecasting. Because price is endogenous, this strand of the literature relies on a dual approach, under which decision makers are profit maximizers, and input and output prices are the only factors deciding output levels (Farrell, 1957). A common conclusion has been that the short-run price elasticity is low or statistically insignificant (see Jensen, 2002 for a review). The use of observed prices as an explanatory variable may be appropriate for large-scale or industrial fisheries if prices are predetermined or otherwise relatively stable. However, fishers in our study do not observe prices prior to a fishing trip, and an alternative assumption about price expectations must be considered.

3 Fisheries and the fresh fish market in Taiwan

Surrounded by the sea, Taiwan is an important fishery player, with capture fisheries ranging from near-shore fisheries (≤ 12 nautical miles) to offshore fisheries (12–200 nautical miles) and distant-water fisheries (DWF). The near-shore and offshore fisheries (hereafter referred to as coastal fisheries) are mostly small in scale (an average crew size of 5.1 people per vessel and 1.4 days per trip), but employ over 50% of the people working in the fishing sector (Fisheries Agency, 2008, 2014). Coastal fisheries catches are highly appreciated by the Taiwanese due to their freshness and the long tradition of fish consumption—the term “hian-lau-a” is used by local people to describe fresh catches just out of the water that have not been chilled or frozen. The market price of ‘hian-lau-a’ is typically higher than that of its frozen counterpart.

Coastal fisheries management in Taiwan primarily relies on license control, except for a few specific fisheries such as the sergestid shrimp fishery (Wu and Ou, 2009). License control was introduced in 1967 and fully implemented in 1991 (Huang and Chuang, 2010). Once fishers obtain a fishing license, they face no effort or catch quotas and are free to exploit the resources, apart from a few protected species. This, however, has come with a price; government statistics show that catches associated with coastal fisheries have been declining steadily from a peak level of 400,000 tonnes per year in the 1980s (Fig.1). The decline is mostly due to reduced landings from the offshore fisheries. The catch share of DWF has been on the rise: from 42% in 1965 to 84% in 2014 (Fisheries Agency, 2014).

The lack of efficient fisheries management in Taiwan is due in part to the high species richness. One implication is that common single-species management tools such as "Total Allowable Catches" (TAC) would be more difficult to implement. While the authorities in Taiwan have introduced several measures to ease fishing pressure, the evidence suggests that these efforts have failed to correct the problem (Huang and Chuang, 2010).

To investigate an individual fisherman's short-term price elasticity, we focus on the multi-species coastal trawl fisheries serving the Ke-Tzu-Liao fish market in Ziguan, southwestern Taiwan.[1] All catches are auctioned soon after landing. The Ziguan Fishery Association is in charge of the auction [2], which follows a standard protocol, including sorting and weighing catches prior to the auction. The auctions follow the Dutch style where an auctioneer starts with a high bid, then lowers the bid until a buyer is found. The market operates daily from 11am–3pm, except for the Chinese New Year. Fishers selling their catches are typically small-scale fishers engaging in daily fishing trips; that is to say, fishers go out to the sea during the night (3–4am) and return to the port during the day when the market opens for auction. There are about 90 fishing vessels registered in the local association. Only registered buyers are allowed to make a bid. As of 2015, there were about 400 registered buyers.

Focusing on the Ke-Tzu-Liao fish market is interesting because the market represents one of the most developed auction markets for fresh fish landings in Taiwan. A functioning auction also ensures that a key economic assumption of an "equilibrium market" can hold. Moreover, the sea southwest of Taiwan (where Ke-Tzu-Liao is located) is an important fishing ground for trawl fisheries. Bottom trawl, often

[1] Ziguan is also spelled Tsukuan or Tzukuan.

[2] All fishers from the area are members of the Ziguan Fishery Association. The role of the association is to provide a market place for its members and to facilitate the sale of fish. It does not enforce any fishing quotas.

considered to be one of the least selective and most destructive forms of fishing, is also the most common fishing gear used for coastal fisheries in the region and many areas of the world (Shen and Heino, 2014; Watson et al., 2006).

4 Theoretical framework

Recursive supply and demand markets

The supply and demand of the fresh catches from Ke-Tzu-Liao follows a recursive structure put forward by Wold (1954). If we apply Wold's theory of a hierarchical causal chain in our model, given the available information (e.g., lagged prices), fishers make target decisions before the actual prices of target species are observed. Let us define a simple recursive system as follows:

$$\text{Supply: } q_t = a_s + b_s E(p_t) + \mu^s, \tag{1}$$

$$\text{Demand: } p_t = a_d + b_d q_t + \mu^d, \tag{2}$$

where a and b are parameters. Supply decisions are based on expected prices $E(p_t)$, which is assumed to be a function of past prices $E(p_t) = f(p_{t-1}, ..., p_1)$, following the cobweb theory (Ezekiel, 1938). The demand of the day determines current prices that clear the market. This will trigger a supply response for the following day and the model continues to operate. Both expected prices in the supply equation and quantity landed (q_t) in the demand equation are exogenous or predetermined, and their parameters have a causal interpretation (Strotz and Wold, 1960).

A recursive system removes simultaneity bias through the introduction of a time unit (a day in our case). However, the simultaneous-equations literature has warned against cases where the problem may still persist. The first case involves low frequency observational data. While simultaneity may not be present in high-frequency (e.g., daily) data due to, for example, a lack of response time, it may still emerge if the available data are averaged over a long period (e.g., monthly or annually). In this case, a static model with simultaneity becomes a limiting case of its dynamic recursive model (Graddy and Kennedy, 2010). The second involves large inventory changes. Roberts and Schlenker (2013) explained that expected prices of agricultural commodities in the supply equation can be endogenous due to an unobserved supply shift caused by changes in the storage level. When inventory changes were small and involved high frequency data (daily trading data from the Fulton fish market), Graddy and Kennedy (2010) showed that their recursive system did not suffer from simultaneous equations bias. Compared to the Fulton market – a consumption market, Ke-Tzu-Liao is a production market where storage is typically not an option due to the extreme perishability of the catches. This has been further confirmed by our on-site observations. Having freed ourselves from a simultaneity problem, we can estimate the supply equation and the demand equation separately and without bias using an ordinary least squares (OLS) estimator, so long as the error terms of both equations (μ_s, μ_d) are uncorrelated. For the purpose of this article, we will only focus on the supply equation.

Fishers' species/location choice

We postulate that the fishers' supply decision involves their selecting target species to maximize their daily expected payoffs. How do trawlers in our study system actually target? In the context of mixed fisheries concerned with multiple vessels, it often seems to be the case that skippers target a wide range of species and exhibit wide spatial movements (Monroy et al., 2010; Rijnsdorp et al., 2011). It is natural to assume that trawlers target species by moving to different locations to search for intended species.

A trawler's spatial behavior has been previously modeled in the discrete location choice framework (e.g., Holland and Sutinen, 2000). Following this tradition, we assume that there are i main species spread over j locations, and one habitat may be shared by several species. We further assume that all species are available in each location but the biomass of each species varies by location: $\mathbf{B}_j = [b_{1,j}, b_{2,j}, ..., b_{i,j}]$. The total biomass of a species summed over all locations ($B_i = \sum^j b_{i,j}$) is a long-term measure and is seen as time-invariant on a daily scale. Fishers plan their catch based on the expected prices of available species $\mathbf{P}^e = [P_1^e, P_2^e, ..., P_i^e, \varepsilon_P]$ and other exogenous variables.

The fisher's location (or species) decision at time t can be expressed as

$$L_j = f(\mathbf{B}_j, \mathbf{P^e}, \varepsilon_B, \varepsilon_P), \tag{3}$$

where ε_B is the measurement uncertainty in expected stock levels at any location, and ε_P is the measurement uncertainty regarding how the expected prices are formed. By dropping the time subscript t, the harvest equation on day t can be expressed as follows:

$$q_{i,j} = g(L_j, \mathbf{I}, \mathbf{W}, \mathbf{D}, \varepsilon_H), \tag{4}$$

where $\mathbf{I}$ denotes composite input prices such as the price of fuel and labour, $\mathbf{W}$ is weather conditions, and $\mathbf{D}$ refers to seasonal and weekday dummy variables. ε_H is a measure of uncertainty in harvesting due to the by-catches. Because the trawling area is relatively small and there is only one monitoring station, we assume that $\mathbf{W}$ is location invariant within our study area.

Combining equations 3 and 4 and summing up catches over all locations, we obtain the following harvest equation on day t:

$$Q_i = \sum_{j=1}^{j} q_{i,j} = \sum_{j=1}^{j} g(\mathbf{B}_j, \mathbf{P^e}, \mathbf{I}, \mathbf{W}, \mathbf{D}, v_i) = h(\mathbf{B}, \mathbf{P^e}, \mathbf{I}, \mathbf{W}, \mathbf{D}, v_i), \tag{5}$$

where $v_i = f(\varepsilon_P, \varepsilon_H, \varepsilon_B)$, and the error terms are independent and identically distributed. Eq. 5 serves as the base of our empirical estimation detailed in Section 5. Because the trawlers in our study area are relatively homogeneous and because there are few vessels relative to the available fishing area, we assume that the harvest equation (Eq. 5), expressed at the level of an individual fisher, also describes the aggregate behavior at the fleet level.

5 Data and estimation strategy

Data

Our analyses are based on a unique dataset on coastal fisheries catches landed at the Ke-Tzu-Liao fresh-fish auction market in southwestern Taiwan (see the online supplement). The data set contains daily landings and daily ex-vessel prices spanning 2001–2015. The data are vessel aggregated, but disaggregated by species or species groups (hereafter referred to as species).

We focus our analysis on the top 12 species that are most frequently caught (available during 95% of the market opening days). Table 1 provides an overview of the data. It is apparent that the variation in the quantity landed is much greater than the price. The price data are standardized to December 2015 prices using the monthly Consumer Price Index (CPI) across all sectors, provided by National Statistics of Taiwan. The annual growth rate of CPI in Taiwan during our study period was about 1.03%. The monthly CPI values were assigned to the 15th of the respective months, and the daily CPI values were estimated from the monthly values using cubic spline interpolation[3]. There are strong negative correlations between the price of the day and the catch of the day across all species.

Among the selected species (Table 1), the group "mixed" is a special category that represents (1) high-value but low-volume by-catch—if the catch of an individual species is below the minimum auction unit (about a 1 kg basket), they are auctioned together with other species in a similar price category; (2) uncommon species that

[3] We also tried linear interpolation of the monthly CPI values. As with the spline interpolation, monthly CPI values were assigned to the 15th of the respective month. The statistical models are not sensitive to the interpolation technique we have used.

are not included in any of the official lists published by the Fisheries Administration. Furthermore, several other species are represented by groups of closely-related species, including "alfonsinos".

Fuel prices were downloaded from the website of Chinese Petroleum Corporation Taiwan, a state-owned company, and deflated using the monthly CPI as mentioned above. The fuel refers to category A fuel for fishing vessels. The prices are weekly because they are adjusted centrally every week to reflect price changes in the international oil market. To account for the effect of weather on fishing, we used data on wave height collected at the Penghu data buoy station (N 22°18.55',E 120° 21.46'), run by the Central Weather Bureau of Taiwan. The data were recorded daily during 2001–2015, with some gaps caused by malfunctions.

Predicting expected prices

We assume fishers follow quasi-rational expectations (QRE) (Nerlove and Bessler, 2001) in determining the expected prices of species. Quasi-rational fishers are only bounded rational, not knowing the exact forecasting model but computing their estimates of future prices based on past observations. In this sensen, QRE represents a more realistic version of the rational expectation that assumes no systematic forecast errors of prices. The rationale behind QRE is that if the prediction of a theory is better than the expectations of agents, then there will be rent-seeking behavior (e.g., offering consulting services to fishers) to take advantage of information asymmetry, eventually closing the gap (Muth, 1961).

The expected price is predicted via the best-fitting univariate ARIMA model detailed as follows:

$$P^e_{i,t} = \eta_1 p_{i,t-1} + \cdots + \eta_k p_{i,t-k} + \varepsilon^0_t + \zeta_1 \varepsilon^0_{t-1} + \cdots + \zeta_n \varepsilon^0_{t-n}. \tag{6}$$

Eq. 6 assumes that the current price of a species (p_t) depends on its past prices

($p_{t-1},\ldots,\ p_{t-k}$), the current random error (ε_t^0) and past random errors ($\varepsilon_{t-1}^0,\ldots,\varepsilon_{t-n}^0$). The coefficients η and ζ correspond to the autoregressive component and the moving average (random errors) component, respectively. Prior to the prediction, we first remove the year and seasonal trend in the price time series, followed by fitting the residuals using the `auto.arima` function in the R library `forecast`. This function uses a variation of the Hyndman and Khandakar algorithm, combining successive KPSS tests for stationarity (Kwiatkowski et al., 1992), and the minimization of the AIC and MLE to obtain an ARIMA model (Hyndman and Khandakar, 2008).

The agronomic literature has shown that market participants may have heterogeneous price expectations (e.g., Chavas, 2000). An assumption of homogeneous price expectations is more justified in our case due to the aggregated data that we use and the relatively simple market structure in Ke-Tzu-Liao.

Vector error correction model and seemingly unrelated regressions (VECM-SUR)

Our empirical model follows the specification in Eq. 5, where all but dummy variables are in log form. Algebraically:

$$Q_{i,t} = a_1 + \Phi_i \mathbf{P}_t^e + \gamma_i \mathbf{B}_i + \delta_i \mathbf{W}_t + \theta_i \mathbf{I}_t + \mathbf{D} + v_i. \tag{7}$$

Both the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test for stationarity and Dickey-Fuller (DF) test for unit root show that the main variables in Eq. 7 are non-stationary and I(1) integrated. Moreover, the residuals of Eq. 7 are serially correlated. It becomes necessary to transform Eq. 7 before performing any estimation. Taking first differences would be sufficient to meet the stationarity condition of I(0), but it removes the long-run effect in the model. Johansen cointegration tests have revealed that the prices and quantities of the same species are cointegrated and their residuals are trend stationary. To utilize this cointegration relationship, we formulate the catch equation in the form of a vector error correction model (VECM). Specifically,

$$\begin{aligned}\Delta \mathbf{Q}_{i,t} =& a_1 + \overbrace{\alpha(Q_{i,t-1} - \beta \mathbf{P}^e_{t-1} - \sigma t)}^{\text{Long-run effect (ECT)}} \\ & + \overbrace{\sum_{p=1}^{K_i} \hat{\Phi}_{1,p} \Delta \mathbf{Q}_{i,t-p} + \sum_{p=1}^{K_i} \hat{\Phi}_{2,p} \Delta \mathbf{P}^e_{t-p}}^{\text{Short-run effect}} + \delta_i \Delta W_t + D_w + \nu_i. \end{aligned} \tag{8}$$

The model above consists of a long-run effect–the error correction term (ECT)–and a short-run effect (Johansen, 1995). All variables in the long-run effect (own quantities, own prices and prices of other relevant species) are treated symmetrically in the VECM. Eq. 8 only represents the model of supply elasticity where quantity (Q) is treated as the dependent variable. The optimal lag K is species-specific. We select K and the cointegration rank simultaneously using command `ca.jo` from R package "urca" (Pfaff, 2008) and `rank.select` from "tsDyn" (Stigler, 2010) following the Bayesian information criterion (BIC). The cointegaration rank can be selected independent of K or simultaneously with K. The latter approach, proved by Aznar and Salvador (2002), was used in the study because it leads to a simpler model. We construct the right-hand side variables manually and run the OLS of each species either independently or jointly in a system equation.

The economic interpretation of coefficients in Eq. 8 is as follows. If the long-run relationship is stable (i.e., $\alpha < 0$), α can be interpreted as the speed of adjustment from an existing disequilibrium; β is the normalized long-run supply elasticity; vector $\hat{\Phi}_2$ refer to lagged short-run own- and cross-price elasticities. δ is the wave elasticity. D_w refers to weekday dummies and ν is the error term satisfying IID.

We use a two-pronged strategy to account for the mixed-species nature of the coastal trawl fishery landing at Ke-Tzu-Liao. First, we account for the effects of other species on the targeting decisions in relation to a particular species: vector P^e includes the expected prices of several species; i.e., $P^e \in [P^e_1, P^e_2, ..., P^e_i]$. Second, there are technical interactions between the species, reflecting the lack of technology to catch species with overlapping ranges separately–a feature of most trawl fisheries. This implies that the error term ν_i across different species-specific catch equations (Eq. 8) may be correlated. We therefore jointly estimate all catch equations using Zellner's (1962) iterative Seemingly Unrelated Regression (SUR). SUR is a way of considering potential multi-output in mixed-fisheries (Pascoe et al., 2007). The SUR analysis is implemented via the R package *systemfit* (Henningsen et al., 2007).

To determine the most relevant species to be included in the catch equation as cross-price effects, we first run Eq. 8 where $\boldsymbol{P^e}$ contains own expected prices only. We then choose the relevant species based on the correlation matrix of the residuals of the catch equations (Fig. 3). In the current analysis, we set the correlation threshold to 0.22, the lowest maximum correlation across all species, so that for each species, at least one cross-price effect is included. For lizardfishes, this rule resulted in more cross-price effects than were estimable. Furthermore, because the high cross-species correlations (Fig. 3) suggest it is primarily a by-catch species, we removed this species from subsequent analyses.

Several time-invariant variables in Eq. 5 are removed in Eq. 8. These include the stock biomass $\boldsymbol{B}$, which is endogenous. $\boldsymbol{B}$ is a latent variable and can be treated as a constant over short (e.g., daily) timescales. In the short-run model, $\boldsymbol{B}$ disappears by differencing; in the long-run ECM model, the biomass effect, if any, is implicitly captured by the trend term (σt) [4]. We remove fuel prices, as well as year and monthly dummies from Eq. 8 due to a lack of statistical power [5]. The sign of the coefficients is expected to be negative for wave height but positive for own prices and lagged own prices.

[4]Note that the ECM model in Eq. 5 does not require t to be linear. Because the trend also captures other long-run effects, we cannot disentangle the effect of biomass.

[5]We tried an alternative model specification by modeling long-term and seasonal patterns as third-degree polynomials, with the day number from the beginning of the study (for long-term trends) or Julian day (for within-year seasonal patterns) as explanatory variables. We did not detect any seasonal or yearly effect in our FD models.

6 Results

Short-run own price elasticity of supply

Because our model estimates the daily price elasticity of supply based on the expected prices predicted by ARIMA, the daily supply elasticity should be interpreted as a percentage change in the weighted sum of past prices. In terms of the own price elasticity of supply (PES), all but one species (the largehead hairtail *Trichiurus lepturus*) exhibit a positive and statistically significant PES (Table 3). The magnitude varies with lags and species, ranging from 0.4 to 1.1 (Fig. 4). Neritic squid (*Abralia multihamata*), Japanese butterfish (*Psenopsis anomala*) and shrimp scad (*Alepes djedabba*) demonstrate elastic price responses in multiple lags. This result is surprising, provided that this is the response within a single fishing day and that fishers were constrained by the limited fishing hours each day. Largehead hairtail is the only species on our list that is not price responsive, possibly because the fishery operating from Ke-Tzu-Liao is not optimized for this species. The low price elasticity found for the mixed category is in agreement with our expectations, because it represents a heterogeneous mixture of valuable by-catch species or uncommon species that cannot be targeted as a single group.

Long-run own price elasticity of supply

The coefficients of the error correction terms (ECT) in all eleven catch equations have the expected negative sign (Table 3), suggesting that there exist stable long-run relationships between quantities and expected prices for all species. The median value of the ECT coefficient is -0.23, meaning that approximately 23% of the total disequilibrium in quantities in Ke-Tzu-Liao was corrected within one effective fishing day. For 10 out of 11 species, it takes no more than seven days for an existing catch disequilibrium to return to its equilibrium state. In other words, the long-run effect here is approximately a weekly effect. The speed of the equilibrium adjustment is also captured by statistically significant but negative coefficients of the lagged catch quantities (Fig. 4), which show that the short-run supply of a fish species is negatively influenced by its landing in the past few days, the more so the closer the lag.

We found that the long-run PES is always greater than the short-run PES of a particular species; the latter is about 18%–66% of the former. This finding is consistent with the literature, namely, fishers become more responsive if given more time flexibility. The largehead hairtail is the most evident case, where the PES of the hairtail is not significantly different from zero in the short-run but rises to 0.63 in the long-run. Four species in our list, namely red bullseye, Japanese butterfish, shrimp scad and neritic squid, have a PES of over 3, implying that every percentage increase of in the expected prices of these species will lead to the catches for the same species increasing by more than three percent. Notice that the most price elastic species, namely the red bullseye (3.8) and Japanese butterfish (3.7), are also the most valuable ones in terms of the mean price (Table 1).

Cross price elasticity of supply

Similar to own-price elasticity, short-run cross-PES is much weaker than long-run cross-PES. We hence focus on the long-run cross-PES hereinafter. The cross-PES separates substitute-in-production from complement-in-production (joint product). A substitute has negative cross-PES, because targeting one species more implies targeting others less; joint products carry positive sign as targeting a species leads to a by-catch of other species sharing the same habitat. In all but one case, the own-PES is larger than the cross-PES (Figure 5). Largehead hairtail, the least price responsive species, is the only species whose catch is more affected by the price changes of other species than its own. The greatest substitute relationship is found between the black snoek and largehead hairtail, where a 1% increase in the price of the snoek leads to a 1.5% reduction in the amount of largehead hairtail supplied.

The red bullseye and red scad are complements for each other, and an increase in the price of alfonsino will reduce the supply of both species. However, the opposite is not true, indicating that they are by-catch species for the alfonsino. The alfonsino is also the species that interacts with most of the other species studied, either as a substitute or as a complement. This may indicate that alfonsino has wide distribution. The interaction of fishing gear probably plays an important role here. Trawling, a predominant fishing method around southwestern Taiwan, is known for low selectivity. By contrast, the Japanese butterfish has no interaction with other species. This may suggest that its distribution or microhabitat differs from those of the rest.

The effect of wave height and other exogenous variables

As expected, we found that local wave height negatively affects daily landings, except for Japanese butterfish (Table 3). Typically, a doubling of the wave height reduces landings by about 40%. This could be caused by a reduction in fishing effort, reduced catchability, or both; without effort data, we cannot disentangle these mechanisms. Species with a strong wave effect include reef-associated species such as shrimp scad (-0.6), red bullseye (-0.41), and redtail scad (-0.47). It is possible that fishing near reefs is more sensitive to weather than fishing species in more open habitats. For 8 out of 11 species, the short-run maximum price elasticity is higher than the wave elasticity. In other words, fishers are generally more sensitive to price changes than to wave height changes if the fish are caught locally.

The weekday dummies showed a degree of cyclical effect in landings for several species. Compared to Monday, 4 out of 11 species have a lower catch volume on Sunday and 6 out of 11 species show higher catches on Tuesday or Wednesday. These effects are the most evident for mixed species and neritic squid. This is probably because some vessels may take a day-off on Sunday, in combination with the lower demand for fresh catches on Sunday and early in a week, and the delay in transporting the fresh fish from the production market to consumer markets and end consumers.

International oil prices underwent a drastic change during our study period, also impacting vessel fuel prices. The effect of fuel price changes on landing appears to be mostly negative but statistically insignificant (not shown in Table 3). The result is in line with what other studies found for industrial-scale fisheries; for instance, Kroodsma et al. (2018) only found very low short-run price elasticity of fuel demand (-0.06) for global fleets (many of which are active on the high seas). Two reasons may explain our result: (1) the fuel price for fishing vessels is subsidized and regulated. It was only from 2008 that the Taiwanese government started to adjust the price weekly to reflect international oil prices; (2) fishers tend to store fuel for later use once the government announces a price increase, and thus they are less immediately affected by price changes.

Robustness

We have performed several diagnostic tests including the Durbin-Watson(DW) test for serial correlation of disturbance, the Ramsey RESET test for model mispecification, and the Goldfeld-Quandt (GQ) test against heteroskedasticity. Our model is able to pass DWtest, GQtest but not RESET test. This is probably due to the outliers present in the data. As a robustness check, we removed observations identified as outliers in the residuals, but the results did not change appreciably.

Similarly, because wave data are unavailable before fall 2006, we analyzed the results with and without wave height. The results are similar in essence, apart from the long-run elasticity of the mixed species category disappearing in the case of the longer dataset. This is likely to have been caused by changes in how the mixed category has been used, and we therefore present the results with wave height included for the period 2007–2015.

7 Discussion

Compared to quota-managed fisheries, the harvest behavior of license-controlled (or limited-entry) mixed fisheries is under-studied, primarily due to limited data availability. This study represents one of the few examples. Our analysis is based on daily dockside catch statistics for trawl fisheries in southwest Taiwan. We found evidence of a price elastic short-run supply for several species. The maximum daily price elasticity of supply (PES) was positive and statistically significant for all but one of the species. The long-run (approximately weekly) PES was greater than one for 8 out of 11 species, reaching a maximum level of 3.8.

This finding contrasts with the previous results from large-scale and quota-managed fisheries, in which the short-term supply of fish is price inelastic (see a review by Jensen). Our results are somewhat unexpected because fishers from Ke-Tzu-Liao operate on a small scale, face narrow reaction windows (short fishing trips) and have no control over fish prices. Moreover, fishers primarily catch fish by trawling, which is a relatively indiscriminate fishing method.

The results from our analysis can be understood in light of fishery characteristics in the studied region. First, a rich mix of species along the southwest coast of Taiwan enables fisheries to engage in what is termed a "portfolio fishing" strategy (Baldursson and Magnússon, 1997). A growing literature uses portfolio theory to explain the fishers' species targeting decisions as a way of diversifying their income sources and reducing income risk (Perruso et al., 2005; Cline et al., 2017). This is all the more so for small-scale fisheries (Finkbeiner, 2015; Anderson et al., 2017). In the case of Ke-Tzu-Liao, because available fishing time is constrained (2–3 hours per day), the only short-term option for increasing revenues and securing income on the day is to preferentially catch more valuable species.

Second, the semi-open access provided by fisheries management in Taiwan gives fishermen the flexibility to fully exploit the species potential in the area. Kasperski and Holland (2013) found that increasing access restrictions between fisheries in the

US have been limiting the fishers' ability to spread their income risk across multiple fisheries. In a system with many interacting species, single species management may create lock-ins that constrain fishers from adapting to unintended consequences (Aguilera et al., 2015). In this sense, fishers in Ke-Tzu-Liao benefit from the slackness of fisheries management in Taiwan, at least in the short-run. In the absence of TAC, there is a risk of over-exploitation in the long-run. Third, the auction market established by the local fisheries association facilitates the transmission of price signals from consumers to fishers in an efficient manner. Consumer's preferences for freshness determines the extreme perishability of the catches. As high-quality catches are rewarded with higher prices, and excessive catches are punished with lower prices, fishers are encouraged to be price responsive.

We emphasize that an auction market, such as the one in Ke-Tzu-Liao, is an exception rather than the rule in Taiwan. In general, coastal fisheries in the region are primarily quantity-driven, often through supply contracts that specify quantity. Quantity-driven fisheries without TAC regulation are more susceptible to overexploitation. Previous studies have documented that auction markets enhance the overall price levels for fishers (Guillotreau and Jiménez-Toribio, 2011). Auction markets together with TACs are the two essential elements underpinning the application of a rights-based co-management system for coastal fisheries in Spain (Molares and Freire, 2003; Macho et al., 2013). Our study suggests that establishing competitive auction markets could be beneficial in alleviating excessive fishing pressure in the region.

Another implication of our study is that one should be cautious when inferring the status of stocks from commercial catches. There is considerable interest among fisheries scientists to use trends in catch data to deduce the status of fish stocks for conservation and the management of data-poor fisheries (Grainger and Garcia, 1996; Froese et al., 2012). Our results show how such trends may also be affected by changes in market conditions (e.g., prices) even in seemingly indiscriminate mixed fisheries; a failure to account for such effects may lead to distorted stock assessments (Pauly et al., 2013; Free et al., 2020).

There are a number of limitations in our study. While having fine temporal resolution, our data are aggregated over space and producers, and contain no information on the daily numbers of active producers. This latter limitation is probably unimportant: the crew salaries are paid at a fixed rate, independent of fishing activities, so vessel owners have an incentive to keep their vessels active. Few of the ‘species’ can be trusted to represent pure biological species. Moreover, lack of stock information prevents us from disentangling the biomass effect explicitly.

To our knowledge, this study is the first one to analyze daily fish price data in order to understand the short-run supply responses of fisheries controlled by licenses only. Our VECM-SUR model accounts for both serial correlations that are typical for data with high temporal resolution and species interactions that are characteristic of mixed fisheries. The results show unexpectedly high responsiveness to the price changes, helping time-limited fishers to maximize their revenues. Our first attempt also points to some interesting directions for future research. In particular, how could knowledge on short-run supply decisions be incorporated into fisheries management? And could the integration of auction mechanisms into existing license controlled management systems help to reduce overexploitation in coastal fisheries?

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Figure list

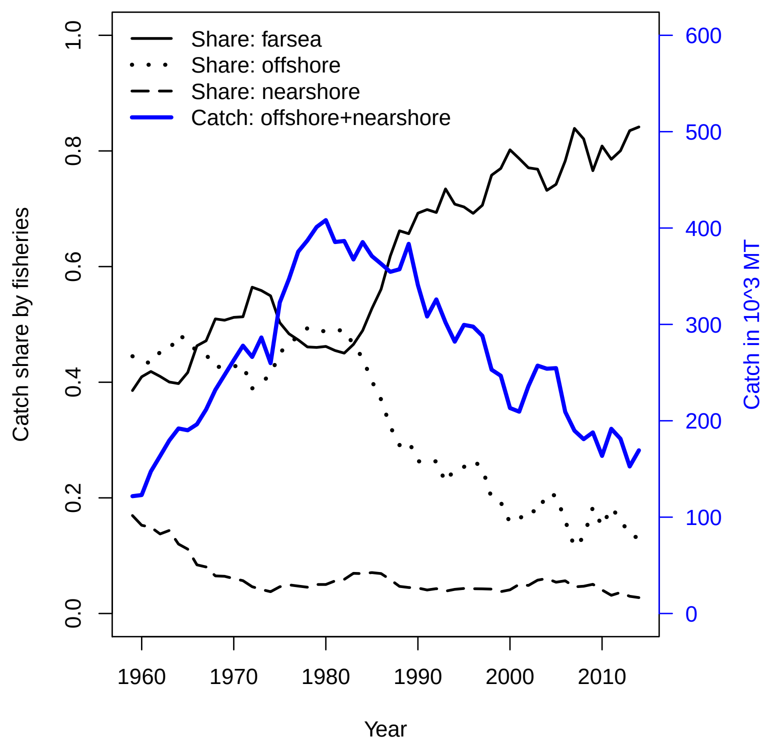

Figure 1: Time evolution of catch proportions in different fisheries (left vertical axis) and total catches from offshore (12–200 nautical miles) and near-shore (3–12 nautical miles) fisheries (right axis) in Taiwan since 1959.

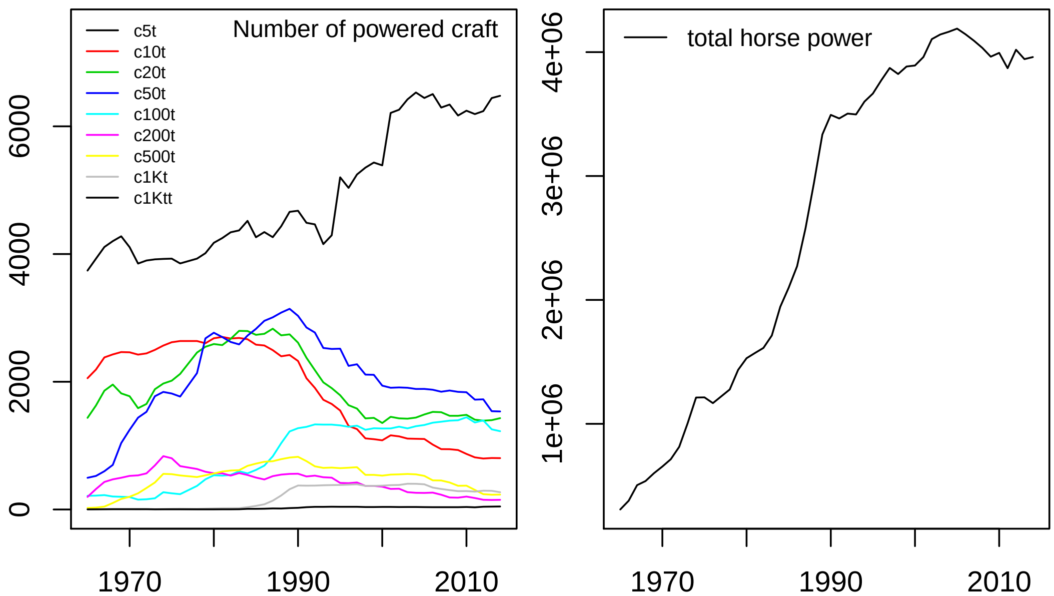

Figure 2: The growth of powered fishing craft measured in numbers (left panel) and aggregate horse power (right panel) across all fisheries in Taiwan. Different curves on the left refer to different vessel groups based on tonnage, e.g., c5t $\in$ (0–5] tons, c10t $\in$ (5–10] tons, c20t $\in$ (10–20] tons, ..., and c1Ktt ≥ 1000 tons. The number of powered craft and total horse power appear to have reached an equilibrium level during our study period (2001–2015).

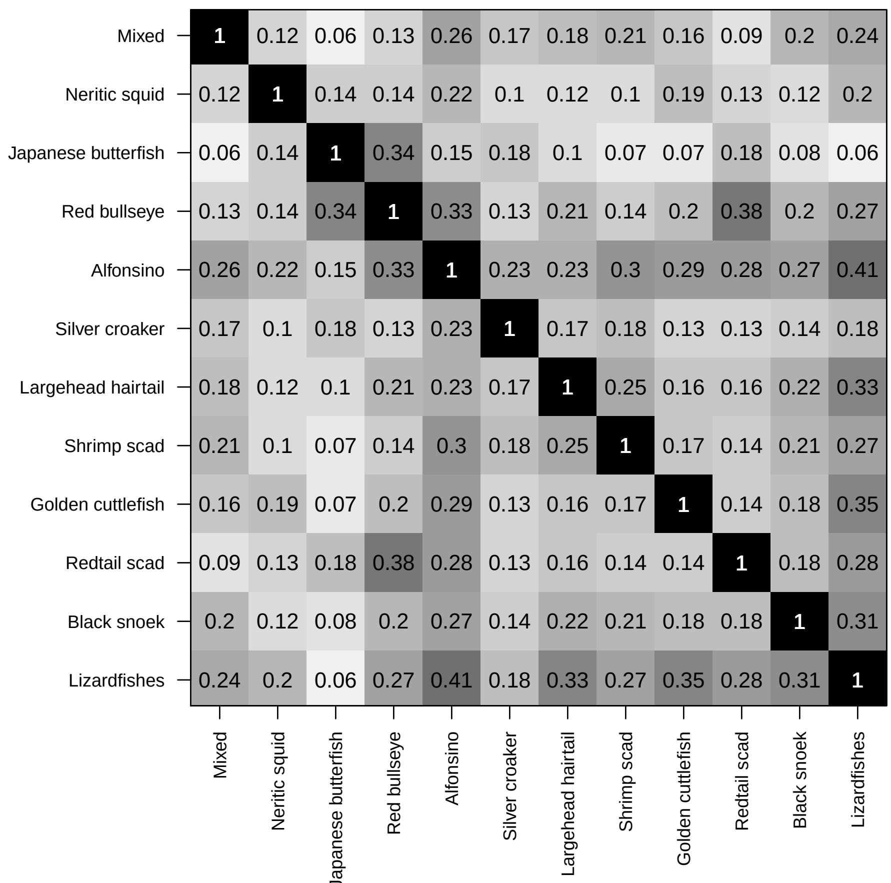

Figure 3: Correlations of residuals for all species pairs in an SUR model for 12 species. For each species, the catch model follows the specification in Eq. 8, except that the expected prices of other species are omitted from the equation. The grey scale is proportional to the strength of the correlation indicated by the numbers.

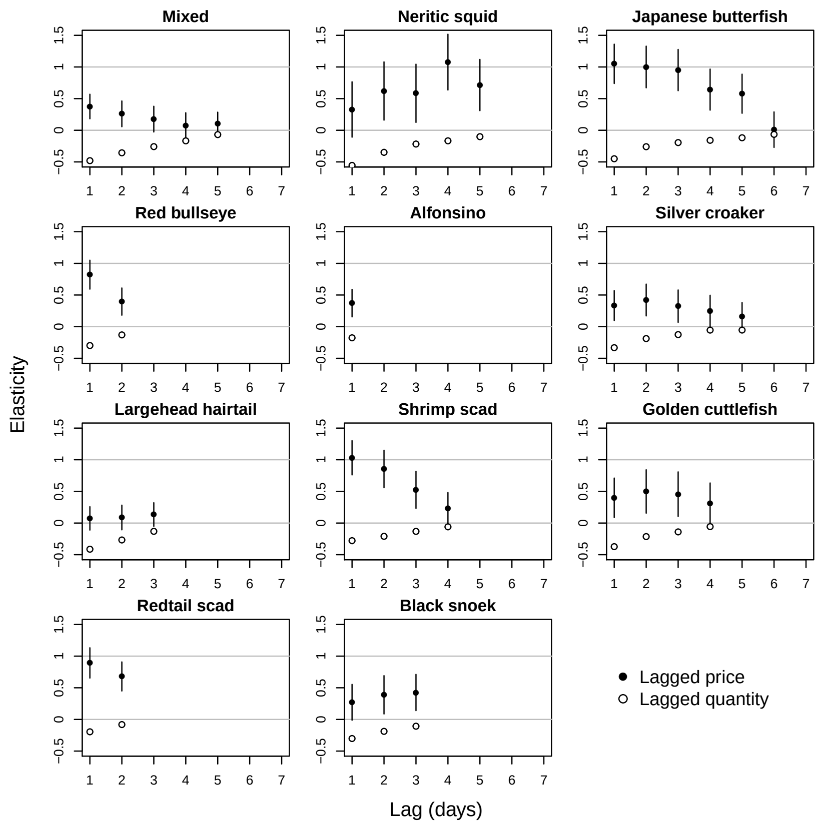

Figure 4: Short-run effects of lagged price and lagged quantity on the daily landed quantity for 11 species. The cointegration rank and the lags were selected simultaneously based on the Bayesian information criterion (BIC) and relevant economic theory.

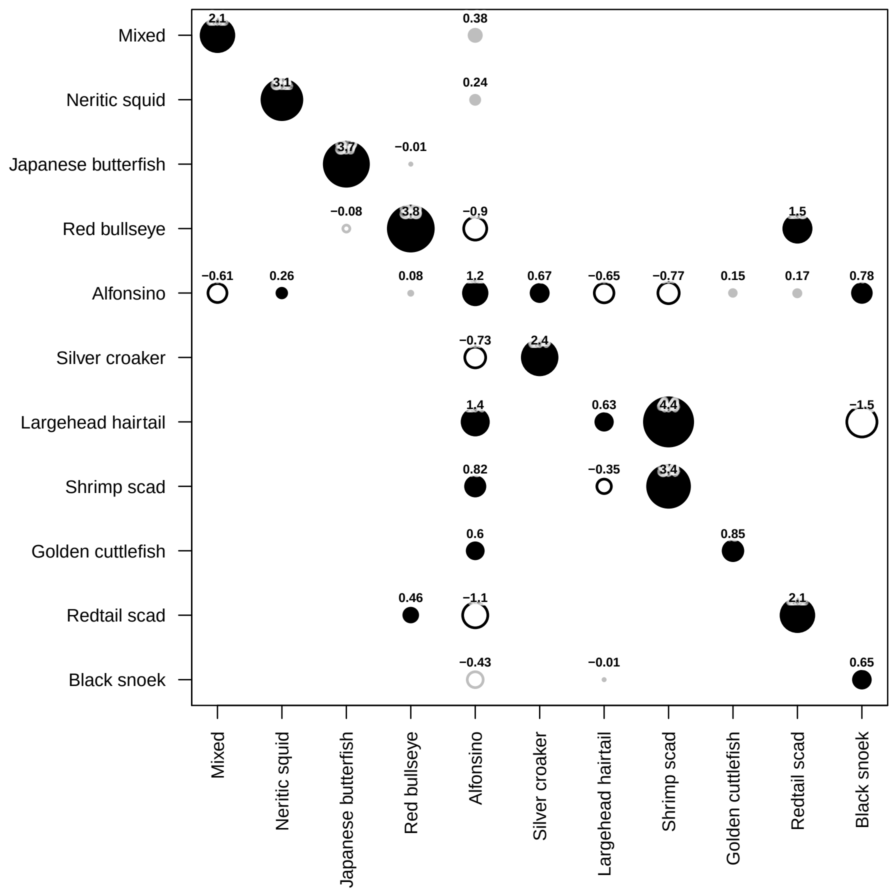

Figure 5: The long-run cross-price elasticity (off-diagonal) and own-price elasticity (diagonal) of supply based on the VECM-SUR model for 11 species. The species for which elasticity is calculated is on the left. Filled circles refer to positive values and empty circles to negative values. Grey circles are statistically not significant. The area of the circle is proportional to |elasticity|.

Table list

Table 1: Data Summary Statistics (2001–2015)

Var.	Unit	Description	N	Mean	SD	CV	Min	Max
Volume	kg/day	Alfonsino	5088	314.8	238.8	0.76	1.0	2332
		Black snoek	5023	90.3	87.9	0.97	1.0	994.0
		Golden cuttlefish	5056	125.0	143.7	1.15	1.2	6437
		Japanese butterfish	5042	543.5	523.4	0.96	0.2	4412
		Largehead hairtail	4987	265.8	309.9	1.17	1.0	4073
		Lizardfishes	5019	138.9	117.8	0.85	1.0	960.9
		Mixed	5109	3228	2958	0.92	1.3	35829
		Neritic squid	5118	1196	2921	2.44	2.9	38225
		Red bullseye	4942	195.1	302.5	1.55	0.9	4358
		Redtail scad	4956	314.3	304.3	0.97	1.0	5390
		Shrimp scad	5014	132.1	150.3	1.14	1.0	1527
		Silver croaker	5039	296.3	323.7	1.09	0.9	9580
Price	NTD/kg	Alfonsino	5088	195.9	62.3	0.32	31.9	471.2
		Black snoek	5023	126.7	47.0	0.37	15.7	561.2
		Golden cuttlefish	5056	124.4	34.2	0.28	28.3	527.9
		Japanese butterfish	5042	225.0	95.4	0.42	23.2	1469
		Largehead hairtail	4987	108.8	53.8	0.49	11.6	525.4
		Lizardfishes	5019	55.2	18.1	0.33	11.5	274.6
		Mixed	5109	135	33	0.25		
		Neritic squid	5118	143	43	0.31		
		Red bullseye	4942	396.1	138.3	0.35	14.8	856.9
		Redtail scad	4956	53.2	28.8	0.54	11.7	386.5
		Shrimp scad	5014	176.9	69.9	0.39	16.0	694.3
		Silver croaker	5039	130.9	64.3	0.49	15.4	884.9
Fuel	NTD/liter	Weekly price	471	17.5	5.78	0.33	8.43	27.3
Wave	cm	Wave height	3826	86.6	51.4	0.59	21.0	552.0

Note: All prices are in December 2015 New Taiwanese Dollars. N denotes the number of observations for each species. 100 NTD is about 3 USD.

Table 2: Species-specific Expected Price Fitted by Non-seasonal ARIMA model

	Alfonsino	Black snoek	Gol. cuttlefish	Jap. butterfish	Lar. hairtail	Lizardfishes
p	3	2	4	2	2	2
d	0	0	0	0	0	0
q	1	2	3	2	2	2
N	3730	3685	3717	3685	3696	3676
	Mixed	Neritic squid	Red bullseye	Redtail scad	Shrimp scad	Sil. croaker
p	2	3	3	4	3	3
d	0	0	0	0	0	0
q	2	1	2	4	3	2
N	3763	3764	3612	3624	3706	3686

Notes: "p"=the order of the auto-regressive model. "d"= the degree of differencing. "q"= the order of moving average. "N"'is the sample size.

Table 3: The supply responses of small-scale fishers based on the VECM-SUR model (partial outputs)

Dep. Var. ΔQ_t	1 Mixed	2 Neritic squid	3 Japanese butterf.	4 Red bullseye	5 Alfonsino	6 Silver croaker	7 Largehead hairtail	8 Shrimp scad	9 Golden cuttlef.	10 Redtail scad	11 Black snoek
$(LR)P^e_{t-1}$	2.12***	3.07***	3.71***	3.85***	1.17***	2.37***	0.63*	3.36***	0.85**	2.13***	0.65**
	(0.34)	(0.28)	(0.41)	(0.2)	(0.13)	(0.24)	(0.23)	(0.31)	(0.27)	(0.17)	(0.21)
ECT	-0.18***	-0.17***	-0.14***	-0.2***	-0.41***	-0.23***	-0.19***	-0.38***	-0.32***	-0.39***	-0.36***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$2\times$ HLD	7.1	7.3	9.4	6.1	2.6	5.4	6.7	2.9	3.5	2.8	3.1
$(SR)\max(\Delta P^e_{t-p})$	0.38***	1.08***	1.05***	0.82***	0.37***	0.42**	0.13	1.03***	0.5**	0.89***	0.43**
	(0.1)	(0.23)	(0.16)	(0.12)	(0.11)	(0.13)	(0.1)	(0.14)	(0.18)	(0.12)	(0.15)
lag p^*	1	4	1	1	1	2	3	1	2	1	3
$\max(\Delta Q_{t-k})$	-0.48***	-0.55***	-0.45***	-0.3***	-0.18***	-0.33***	-0.41***	-0.28***	-0.37***	-0.2***	-0.3***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
lag k^*	1	1	1	1	1	1	1	1	1	1	1
Wave	-0.29***	-0.11*	0	-0.41***	-0.36***	-0.46***	-0.48***	-0.6***	-0.28***	-0.47***	-0.49***
	(0.03)	(0.05)	(0.06)	(0.06)	(0.04)	(0.07)	(0.05)	(0.06)	(0.05)	(0.07)	(0.06)
Tue	0.09**	0.17**	0.08	-0.1	0.14**	0.33***	0.12*	0.07	-0.04	-0.02	0.02
	(0.03)	(0.05)	(0.06)	(0.06)	(0.04)	(0.07)	(0.05)	(0.06)	(0.05)	(0.07)	(0.06)
Wed	0.13***	0	-0.03	-0.05	0.06	0.15*	0.06	0.15*	0.08	-0.05	-0.04
	(0.03)	(0.05)	(0.06)	(0.05)	(0.04)	(0.07)	(0.05)	(0.06)	(0.05)	(0.07)	(0.06)
Thu	0.06	-0.07	-0.03	-0.1	0.05	0.05	0	0.03	0.01	-0.03	-0.12*
	(0.03)	(0.05)	(0.06)	(0.05)	(0.04)	(0.07)	(0.05)	(0.06)	(0.05)	(0.07)	(0.06)
Fri	0.08*	0.04	-0.05	-0.12*	0.08	0.21**	0.06	0.05	0.09*	-0.06	-0.06
	(0.03)	(0.05)	(0.06)	(0.05)	(0.04)	(0.07)	(0.05)	(0.06)	(0.05)	(0.07)	(0.06)
Sat	0.07*	0.05	-0.05	-0.13*	0.09*	0.08	0.05	0.02	0.14**	-0.03	-0.03
	(0.03)	(0.05)	(0.06)	(0.06)	(0.04)	(0.07)	(0.05)	(0.06)	(0.05)	(0.07)	(0.06)
Sun	-0.09**	-0.24***	-0.23***	-0.06	-0.02	0.04	0.06	-0.01	-0.05	-0.03	-0.16**
	(0.03)	(0.05)	(0.06)	(0.06)	(0.04)	(0.07)	(0.05)	(0.06)	(0.05)	(0.07)	(0.06)

Notes: The model is estimated based on the specification in Eq. 8. "***","**", and "*" represent p values significant at the 0.1%, 1%, and 5% levels, respectively. Standard errors are in parentheses. "LR" and "SR" are long-run and short-run own-PES. "HLD" refers to the half-life-disequibrium, the number of days it takes for an existing disequilibrium to be reduced by half; "lag p^*" and "lag k^*" indicate respectively the corresponding lag position with the maximum coefficient for ΔQ_{t-p} and ΔP^e_{t-k}. Fig. 4 shows the coefficients for all lags.