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Price Transmission between Energy and Fish Markets: Are Oil Rates Good Predictors of Tuna Prices?

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Abstract :

Because most food processes are fossil fuel–based, many food markets are more or less connected to the oil market. Fishing technology in the high seas being energy-intensive, higher oil prices should affect the fish markets. This research looks at price transmission between marine diesel oil and a global fishery commodity, frozen skipjack tuna (Katsuwonus pelamis) through a time series analysis combining four different methods to look for possible structural breaks and regime shifts in the relationship (Bai-Perron, Lavielle, Gregory-Hansen, Markov-switching). Our results prove that the long-run equilibrium between both prices is weakening after the turn of the 2010s. Explaining the drivers of change is of great interest for short-term forecast but also to build long-term scenarios where both supply and demand variables are likely to affect tuna markets.

1 Introduction

In a world of uncertainty characterized by significant environmental, economic and geopolitical changes, forecasting commodity prices remains a difficult though stimulating and necessary challenge for economists [Asche et al. (2016), Gordon (2020)]. Most food processes in the 21st century use energy-intensive technologies and bunker costs represent a major expense in fish supply chains. This is the case for high-seas fishing targeting tuna species [Parker et al. (2015), Basurko et al. (2022)]. We should logically observe a high degree of transmission between oil rates and tuna prices (Yahya et al., 2019).

Tuna prices are highly volatile in a globally integrated market (Jiménez-Toribio et al., 2010). The historical volatility was estimated to 26% and the coefficient of variation for tuna landings amounted to 76%, on the same range as salmon production (Dahl and Oglend, 2014). Tuna prices have more than trebled over the past two decades (2000-2017) whereas the oil price has only doubled, but both products are passing through ups and downs. Tuna catches and trade are subject to many drivers and stressors, such as increasing fishing effort, the use of Fish Aggregating Devices (FADs), ENSO events, trade policy changes, new fishery management rules implemented by Regional Fisheries Management Organizations, exchange rate movements, demand shocks, population and economic growth in emerging countries, etc. [Miyake et al. (2010), Maury et al. (2017), Scherrer and Galbraith (2020), Bell et al. (2021)].

Economic knowledge about tuna markets improves gradually [Herrick Jr and Squires (1989), Squires et al. (2006), Jeon et al. (2008), Guillotreau et al. (2017), Sun et al. (2019)], but is still far from being sufficient to accurately forecast the future prices of tuna several months, years or even decades ahead. In particular, the linkage between the energy sector and the fishing industry is overlooked in the existing literature, with a few rare exceptions [Tyedmers and Parker (2012), Parker and Tyedmers (2015), Guillen et al. (2016)]. However, the existing literature deals more with the energy returns of fishing than about the relationship between the cost of energy and the price of fish. This latter question is nonetheless important to understand the economic drivers of the fishing effort and their impact on the dynamics of global fisheries. In particular, long-run scenarios need to rely on simple but robust economic models to test for the long-term consequences of severe impacts affecting social and ecological systems [Dueri et al. (2016), Maury et al. (2017), Mullon et al. (2017), Bell et al. (2021)]. For example, if lower catches cannot fully supply the growing market demand any longer, prices may increase proportionally, so as to leave the fishers' income unchanged (Sun et al., 2017)? Conversely, if the catch becomes lower with constant prices, an increasing energy cost may deter fishers to maintain the same level of effort, hence relaxing the pressure on stocks. On a more theoretical ground, the relationship between the oil and fish markets is also interesting because the optimal exploitation rules of an exhaustible and renewable resource are different. The Hotelling rule applied to the optimal exploitation of exhaustible resources equalizes the growth rate of prices to the discount rate, under a finite time horizon. For a renewable resource like wild fish, the marginal productivity of stocks added to a marginal stock effect on the fishing rent must be equal to the discount rate at the optimum level of exploitation over an infinite time horizon. Any increase of the discount rate can have opposite effects on extraction rates, accelerating the exhaustion of oil reserves but preserving the renewable stocks at a higher level of biomass, hence resulting in higher catches and lower fish prices (Hannesson, 1986). Fish markets, whose demand is often found price-elastic, would therefore face a fast-growing price of oil energy beyond the peak oil, thus creating a potential price squeeze that would affect the profit margins of the fishing industry.

Despite the intensive use of energy in many food production processes, research works analyzing the link between both markets are not very common [Yahya et al. (2019), Dahl et al. (2020)]. This is why our research contributes to the empirical literature by analyzing the co-evolution of energy and fish prices. In particular, we selected a procedure combining various time series techniques to determine possible break dates in the two markets separately, and in their relationship. Because the efforts of analysts attempting to predict the price of commodities several months ahead are rather concentrated on the oil market, the idea is to test for the long-run relationship between the price of Marine Diesel Oil (MDO) and the price of skipjack (*Katsuwonus pelamis*). If a long-run relationship can be found between the two markets, and according to the direction of the Granger causality, we could be in a position to predict confidently the evolution of the skipjack price from the oil Futures market. More precisely, by looking at the relationship between both markets, we hope to learn whether any actual influence of the oil price on the skipjack price is passing through the supply-side (energy being a major component of the marginal cost of fishing) or the demand-side for these two global natural resources [Mullon et al. (2017), Maury et al. (2017)]. The oil market being global, just like the market for canned tuna through which skipjack is mostly traded, the dynamics of both prices might well be linked to the worldwide demand growth, just like many other food commodities [Yahya et al. (2019), Dahl et al. (2020)].

The following article is organized as follows. First we propose a literature review about the link between oil and commodity prices to show the importance of the issue at stake regarding tuna markets. Secondly, we developed a time series analysis combining different techniques on monthly prices between 2000 and 2020 to scrutinize the link between the fish and oil markets and look for possible breaks in the relationship. In a following section, we search for other candidate variables to introduce a possible regime shift explaining the dynamics of the skipjack market. Finally, we discuss the results in a last section with regard to the input requirements of holistic models dealing with the future of tuna fisheries under global change scenarios.

2 Literature survey

An increasing number of research works attempts to model the global food demand scenarios for the 21^{st} century [Valin et al. (2014), Bodirsky et al. (2015), Flies et al. (2018)]. In particular, the authors try to do so in order to assess the consequences of reference climate scenarios[1] on food production and consumption levels. Food models are influenced by many different drivers such as real income and prices, but also trade policy changes, population growth and characteristics, the diet patterns, urbanization, and of course by the availability of commodities on the supply side (Valin et al., 2014). This is all the more true when it concerns wild and common resources such as fishery products. Climate change is expected to transform profoundly the level of biomass and the spatial distribution of fish populations, justifying the interest of modelling global demand for fishery products to better understand its long-run drivers [Maury et al. (2017), Scherrer and Galbraith (2020), Mullon et al. (2017), Bell et al. (2021)].

Two classes of models are mostly used to forecast food demand: partial equilibrium models and computable general equilibrium (CGE) models. The latter models are based on utility functions being maximized under the budget constraint to derive the demand functions where households can substitute all types of consumption goods. Consequently, such models require a tremendous amount of data and often rely on strong assumptions regarding the consumption behavior of households. Partial equilibrium models apply reduced forms of demand functions to a limited set of goods (Flies et al., 2018). If the second class of models seems more limited in scope, it allows for greater details about the bundle of goods included in the model (e.g. several fish species), the substitutability between them and the set of determining factors (Guillotreau et al., 2017).

Beyond the interest of understanding food demand drivers, the modelling efforts concerning the demand for wild-caught fish show the interest of unveiling the flexibility coefficients which represent key market-incentives for fishery management. The effort reduction which is required to adjust the fishing capacity to the sustainable level is more likely to be accepted if the price response allows fishers to earn more by catching less and conversely [Sun et al. (2017), Sun et al. (2019)]. Tuna fisheries offer a perfect illustration of a global commodity being harvested in the three oceans, supplying the canning industry with large quantity of raw materials, and being traded as a major source of fish proteins in many countries around the world [Miyake et al. (2010), Mullon et al. (2017)]. The market is global and all regional markets are now quite well integrated under the leading role of the Bangkok market [Jiménez-Toribio et al. (2010), Sun et al. (2017)]. This market presents the valuable advantage of its central position between two oceans and its vicinity to the most productive fishing grounds in the world (Miyake et al., 2010).

Like for any other ocean-wide fishery, tuna fishing and trade are highly dependent on energy-consuming industrial fleets, particularly because of an increasing distance from ports to fishing grounds (Tickler et al., 2018). The conventional index assessing the high level of catch dependence to energy is the Fuel Use Intensity (FUI) measuring the ratio of consumed oil Litres per tonne of landed fish. Across a great number of species and world regions, the mean FUI found by Parker and Tyedmers (2015) since 1990 was 706 $L*t^{-1}$. A study reported an average FUI value of 368 $L*t^{-1}$ for the global purse-seine fleet targeting skipjack and yellowfin tuna (Parker et al., 2015). Two more recent and accurate research works based on vessel data looked at the FUI of the European purse-seine fleet fishing tuna in the Indian Ocean showed a variable FUI value, oscillating between 390 and 680 $L*t^{-1}$ since 2015 according to the level of catches, fishing effort (quantitatively and qualitatively) and vessel size [Chassot et al. (2021), Basurko et al. (2022)]. Keeping in mind an average marine diesel oil price of \$554 t^{-1} between January 2018 and October 2020 and a conversion factor of 0.72 kg per Litre, the fuel cost would reach nearly \$200 per tonne of fish with a $500L*t^{-1}$ FUI. The average price of frozen skipjack being \$1468 per tonne for the same period[2], the energy cost would represent 14% of the ex-vessel price of frozen tuna. Bunker costs are undoubtedly an important component of expenses for purse-seiners targeting skipjack tuna. The share of energy costs is estimated between 20% and 30% of operating costs, depending on the level of oil rates (Miyake et al., 2010). This proportion could even rise up to 50% (Parker and Tyedmers, 2015) or more in case of extremely high prices on the oil market as it happened in September 2008 when the crude oil barrel skyrocketed at \$147 per barrel, just before the financial crash (Tyedmers and Parker, 2012).

The high share of fuel expenses in operating costs legitimates the issue of price transmission between oil and food markets [Avalos (2014), Dillon and Barrett (2016), Su et al. (2019)]. Oil prices and food prices can interact through at least two channels: directly through the trade-off between biofuel energy and agricultural markets, indirectly through oil energy as major input for most food products (Su et al., 2019). The relationship is not straightforward because of this dual influence and some articles bring evidence with a VECM and impulse-response models that oil prices may even adjust to the long-run relationship with corn prices rather than the expected opposite causality (Avalos, 2014). Interestingly, in this study, the relationship has become narrower after that a US Energy Policy Act has made ethanol the only allowed standard additive of gasoline, thus creating a dependence between the oil price and the ethanol (hence corn) price.

However, using Partial Equilibrium frameworks may overlook the macroeconomic effects of oil prices on food markets. Using a global CGE model, some authors have shown that energy prices have also an impact on real income and trade balances (Gohin and Chantret, 2010). The effect would be positive for crude-oil producing countries, but negative for oil importing countries. The authors simulated a 20% reduction shock in world oil reserves and found evidence of a negative relationship between world food and energy prices, countervailing the cost-push effect of an oil price change to food prices. However, one could turn the macroeconomic effect upside down and also hypothesize that an increasing oil price is the result of global economic growth which could somehow benefit to food prices in general, and fish prices in particular. Whatever the channel of pass-through from oil prices to skipjack tuna prices, either as a marginal cost-push mechanism, or a demand-pull process affecting both oil and fish markets, we believe that the relationship deserves a thorough analysis through time series and through a variety of empirical models based on cointegration theory (Johansen, 1988). First of all, a positive correlation and causality found between oil rates and fish prices, if ever demonstrated, could be used to forecast the tuna price as input for canneries with the underlying support of Futures oil market contracts, as proved in other global fish markets like the salmon market (Asche et al., 2016). Secondly, a long-term linkage between oil prices and tuna prices may also be an interesting contribution to a more prospective analysis of global food demand with respect to the peak oil and climate-driven scenarios. What can be the future of the large-scale tuna fisheries if high fishing costs and price elasticity of final demand hamper the profitability of purse-seine vessels and canneries (Sala et al., 2018)? Thirdly, if the relationship appears not to be robust enough in the long term, it might reveal some structural changes and regime shifts that could be meaningful to better understand the price formation on the global tuna markets. Besides the influential status of oil for many food commodities, what is the role of landings or substitute species in the fishery markets, keeping in mind that the world is facing a maximum supply of 80 or 90 million tonnes of wild-caught fish for more than three decades, this supply being now threatened by the global warming process going on and the lack of stringent regulation (Scherrer and Galbraith, 2020). In parallel, the world population is still growing with a higher level of income per capita and requires an increasing amount and diversity of food proteins. What we propose in this research is to reconcile the partial and general equilibrium hypotheses about the link between energy and fish markets by applying a parsimonious cointegration model of price transmission between the oil and fish markets. To that end, we adopt an original procedure combining various structural break searching techniques. First, we check the existence of a long-term equilibrium relation between the marine diesel oil price and the skipjack tuna price. Secondly, we look for structural break dates in the two markets separately, and then jointly by different econometric means. By doing so, we expect more robust outcomes and confidence about the identification of break dates. Thirdly, we investigate the supply or demand-sided nature of the long-term relationship between the two prices by considering other factors affecting the tuna market.

3 Relationship between the prices of skipjack and marine diesel oil

3.1 Data

The monthly price of skipjack (Pskj) is extracted from the FFA Fisheries Development Division using the Thailandese customs database from January 2000 to September 2020 (249 obs.)[3]. The price of Marine Diesel Oil (Pmdo) in Singapore is also supplied by the FFA Fisheries Development Division with data published by Bunkerworld[4] from January 2000 to May 2018. Between June 2018 and September 2020, the series is complemented by the estimated price obtained from a robust long- term relationship existing between the MDO in Singapore the New York Harbor No. 2 Heating Oil Future Contract 4[5]. Both series are transformed by their logarithm to test for the quality of price transmission in the long run (Fig. 1 and Table 1). Table 1 is complemented by the descriptive statistics of two other time series (the price of yellowfin tuna (*Thunnus albacares*) -Pyft- and the quantity of skipjack imports in Thailand -Qskj- measured in metric tonnes, that will be used later in the study to enrich the price transmission model). These two series are extracted from the same database of Thailandese customs.

Insert here Fig. 1 Prices of skipjack in Bangkok and MDO in Singapore (USD/t)

Insert here Table 1 Main statistics

First of all, we check that all series are I(1), in particular for Pmdo and Pskj. This is the case from ADF, ADF-GLS and KPSS tests[6]. Seasonal unit roots needed also to be scrutinized in the following equation suggested by Miron (1996):

$$\mathrm{y_t} - y_{t-1} = \mu_1 D_1 + \mu_2 D_2 + ... + \mu_{12} D_{12} + \epsilon_t \tag{1}$$

where y_t is the time series under investigation, and D is a (monthly) seasonal dummy variable. In the case where the residual term does not contain any information on seasonality, we may consider the Fisher test and the R^2 value associated to each regression as giving an indication about the deterministic seasonality. For the price of skipjack series, this R^2 value is close to 0.10 and even found lower for the price of marine diesel oil (0.05). We can conclude that there is no deterministic seasonality nor deterministic trend in the series [Franses (1991), Beaulieu and Miron (1993)].

The price of skipjack looks also quite volatile. Looking at the annualized standard deviation of log price returns between February 2012 and September 2020 gave a historical volatility of 0.26, which is exactly the same value found in Dahl and Oglend (2014) over the period January 1990-December 2012. This volatility of skipjack tuna monthly prices is comparable to that of the farm-bred Norwegian salmon export price in USD per kilogram (source IMF) between February 2012 and September 2020, i.e. 0.29. The long-term relationship was then tested in a second step but without any success. The null of no cointegration could not be rejected (p-value=0.35) over the whole sample. We assumed that the relationship between the two market prices could have been distorted in the course of time.

3.2 Looking for structural breaks

Long time (monthly) series running throughout several decades can be affected by disrupting events, as observed in other fish markets [Asche et al. (2013), Smith et al. (2017)]. Consequently, we suspected the relationship between the price of skipjack and that of MDO to have been modified during the sampled period. To search for structural breaks, we first used the Lavielle segmentation procedure based on the maximum likelihood criteria with the R-package segclust2d [Lavielle (2005), Patin et al. (2019)]. With a L_{min} of 24 months (minimum length of a segment) and $K_{max} = 7$ (maximum number of breaks), we tested the two series separately. For the oil price, the optimal number of breaks was 3, hence 4 segments (breakpoints: July 2004, December 2010 and November 2014). For the price of Skipjack alone, only one break was found in February 2007 [7]. However, the break dates did not match between the two series. A joint segmentation was then performed with the two series simultaneously and gave one single breakpoint (i.e. 2 segments) in July 2004. According to the International Energy Agency, demand for oil grew at its strongest pace in almost three decades in 2004, mainly driven by supply bottleneck and strong economic growth in Asia and America. The market was also tense because of uncertainty about the security of oil supplies during the second Gulf war (ECB monthly Bulletin, May 2005).

The cointegration equation including a break in July 2004 was then successfully tested with a price transmission elasticity of 0.41, and an increasing intercept after July 2004 ($R^2 = 0.64$). This is in line with the result obtained on a truncated sample of the same monthly data (from 2000:02 to 2015:02) by (Nadzon, 2016), who found an elasticity of 0.64 and a $R^2 = 0.73$ with a Fully-Modified Least Square method (Nadzon, 2016). However, the structural change could also concerned a shift in the slope of the relation. A Gregory-Hansen test was therefore performed to look for the right specification (Gregory and Hansen, 1996). Such models allow to determine when the unknown breakpoints occur (looking at the stationarity of the residuals through the minimum value of the ADF statistic corresponding to the date), and if the latter affects the constant, the trend or the slope in the regression model, thus explaining the absence of cointegration. Their model (4) was selected as the best one, with a shift in both the constant and the slope with no trend (Gregory and Hansen, 1996):

$$\mathrm{l_{Pskj,t}} = \alpha_0 + \alpha_1 \times I(t > \tau) + \beta_1 \times l_{Pmdo,t} + \beta_2 \times l_{Pmdo,t}, \times I(t > \tau) + \mu_t \quad (2)$$

The ADF test procedure gave a breakpoint in September 2010 ($t - stat = -5.171$ with $AR\ lag = 2$), while the Phillips procedure pointed at a breakpoint in March 2007 with $z_t = -4.986$ and $z_a = -45.343$. Including either break date in the model, the two series became cointegrated. However, the Gregory-Hansen model (4) showed no significant parameter estimates for the break of March 2007 on the constant term or the slope, unlike the break of September 2010. Consequently, only the first breakpoint of the ADF procedure (i.e. September 2010) was considered and tested in the following cointegration model:

$$\begin{aligned} \widehat{\mathrm{lPskj}} &= \underset{(9.181)}{3.748} + \underset{(2.427)}{1.572} \times I(t > 129) + \underset{(7.727)}{0.516} \times lPmdo \\ &\quad - \underset{(-1.934)}{0.200} \times lPmdo \times I(t > 129) + \hat{\mu}_t \\ T = 249 \quad \bar{R}^2 &= 0.7383 \quad F(3, 245) = 52.938 \quad \hat{\sigma} = 0.202 \end{aligned} \quad (3)$$

(z-value in brackets; $\tau(129)$ = September 2010)

The τ-stat of the ADF test for $\widehat{\mu_t}$ was -5.12 (p=0.000), proving the long-term relationship (cointegration) between the two variables. However, the difference between the two prices increased and the price transmission elasticity fell significantly from 0.52 to 0.32 after the breakpoint, meaning that the MDO price is less well transmitted to the tuna price after this date. The worldwide economy increased again after two years of crisis, boosting the crude oil price between September 2010 and April 2011. On the tuna market side, this coincided with a period of stable catches (around 2.5 million tonnes between 2006 and 2011), hence lower imports of frozen skipjack in Thailand and higher prices. An error-correction model (VECM) was also tested. The coefficient of the cointegrating vector for lPmdo is 0.530 and the adjustment vector shows a weak exogeneity on the MDO market side, as expected. The skipjack price difference equation of the VECM can be written as follows:

$$\Delta\ \mathrm{Lpskj_t} = -\underset{(-4.697)}{0.118}\ \widehat{\mu_{\mathrm{t-1}}} + \underset{(6.141)}{0.361}\ \Delta\ \mathrm{Lpskj_{t-1}} + \mathrm{u_t}$$

$$T = 247 \quad \bar{R}^2 = 0.168 \quad \hat{\sigma} = 0.077 \tag{4}$$

(t-stat in brackets)

To summarize the results of this section, the dynamics of skipjack prices alone has changed in February 2007. The pattern of the MDO price has changed several times over the period, but particularly in July 2004 which has modified the trajectory of its influence on skipjack tuna prices (intercept of the cointegration relation). Finally, another major break was found in September 2010, changing even more deeply the long-run equilibrium between the two prices (constant and slope of the relation). It seems important to investigate what could be the changes on the two markets and the factors affecting the long-run relationship between both markets.

3.3 A weak prediction of the skipjack price

From the cointegration model and the VECM, we try to simulate the price of skipjack from the single mdo price variable to see whether the latter could represent a trustful predictor of tuna prices. To this end, we generate random errors of the VECM from a normal distribution $\hat{u}_t \sim \mathcal{N}(0, \hat{\sigma}_u^2)$ to first simulate the $\Delta lPskj$ from Eq.(4). Since we know for each time step $lPmdo_{t-1}, lPskj_{t-1}$, and $\widehat{\mu_{t-1}}$, we can simulate the level of lpskj ($= lPskj_{t-1} + \Delta lPskj$) from the current and following periods. The skipjack price is simulated from April 2000 to September 2020 and displayed in Fig. 2, along with the actual skipjack price and with the break of September 2010.

Insert here Fig. 2 Prediction of the skipjack price (in USD/t)

As seen in Fig. 2, if oil rates may represent reasonable predictors of current skipjack price at the beginning of the period, the gap between actual and simulated prices increases for some periods, and particularly after the break of September 2010. This would indicate that the long-run relation evidenced by the cointegration model does not hold tightly for every period. Presumably, a growing demand in the mid-2000s on the oil market resulting in a steady price increase before the crash of August 2008 combined with a stagnation of skipjack catches may have affected the long-run relationship between the two prices. In order to clarify this assumption, additional information needed to be included in the model, in particular to account for the supply of the tuna market. Thailandese imports of frozen skipjack were collected on a monthly basis since this country represents nearly half of worldwide imports reported by FAO and one fifth of global catches of skipjack. The series was found $I(0)$ but more importantly, a Zivot-Andrews unit root test detected several breaks in the series. Consequently a VAR model with one lag, according to the AIC, BIC and Hannan-Quinn criteria, was tested and gave the following results for the first equation with lPskj as the dependent variable:

$$\begin{aligned}\mathrm{lPskj_t} = \underset{(0.692)}{0.172} + \underset{(20.860)}{0.877}\ lPskj^{***}_{t-1} + \underset{(1.620)}{0.034}\ lPmdo_{t-1} + \underset{(2.217)}{0.045}\ lQskj^{**}_{t-1} \\ + \underset{(1.671)}{0.036} \times I(t > 129)^{*} + u_t\end{aligned} \tag{5}$$

$$T = 248 \quad \bar{R}^2 = 0.93 \quad F(1, 243) = 4.919 \quad \hat{\sigma} = 0.101$$

$^{*},^{**},^{***}$, significant at 1%,5%,10% levels, t-stat in brackets.

After the introduction of the lagged quantity variable, the oil price became non-significant, as if the Bangkok tuna price was responding more to the past level of landings than to the oil input price. Unfortunately, the own-price flexibility coefficient did not show the expected sign, i.e. normally negative and unitary as found in previous studies (Sun et al., 2017), presumably because of an identification problem. The level of catch and landings is also possibly affected by the oil rate itself, because the lQskj equation of the VAR system had a very significant parameter estimate for the lagged lPmdo variable. The level of landings could certainly be affected by the energy cost of fishing beyond a threshold, but there may be some other explanation behind the degraded correlation after the breakpoint and the alternate periods of good and bad connections between the two markets. This needed to be scrutinised with potential regime shifts between some sub-periods. In a preliminary conclusion, we consider that the oil price, although influential for the skipjack price, is not a good predictor of skipjack prices for every period.

4 Introducing a regime shift in the oil-tuna price relation

The previous analysis of structural breaks emphasizes the changes affecting the long-run relationship between the skipjack price and the fuel price. We are therefore looking for other possible candidates to explain the evolution of skipjack prices along with the oil price. In particular, the leading role played by a substitute species (yellowfin tuna, *Thunnus albacares*) was pointed out by another study about price cointegration (Jiménez-Toribio et al., 2010). The correlation between the two prices is clearly observed in Fig. 3, with a higher price of the big yellowfin, hence more targeted by purse-seiners, because of a better yield of raw materials per fish for canneries.

Insert here Fig. 3 Skipjack and yellowfin tuna prices in the Bangkok market (in USD/t)

It was therefore decided to test for the relationship between the prices of the two major cannery-grade tuna species before including them in a Markov chain model which allows two regimes of price relationship between the fuel and the skipjack prices, assuming that the change may not be permanent but shifting between two regimes as observed in other fish market studies (Asche et al., 2013).

Confirming the results of the 2010 study, which was based on a sample between January 1995 and December 2006 (Jiménez-Toribio et al., 2010), a cointegration relation was easily found between the two I(1) series of the logarithmic prices of skipjack and yellowfin[8]. A VECM model proved the weak exogeneity of the yellowfin price, the skipjack price reverting back to its long- run relationship with the price of the other species (with a speed of adjustement of -0.1317, significant at the 1% level) while the former one is significant but positive, thus not moving back to the long-run relation. We also assumed that the transition probabilities between the two regimes are depending on the skipjack landings, since the quantity of skipjack, which is prevailing in the Bangkok market (Sun et al., 2017), showed some kind of influence over the skipjack price in the previous VAR equation.

The two regimes shown were then estimated on a sample 2000m1-2020m9 with Eviews 11 (full results in Appendix):

Regime 1:

$$\mathrm{lPskj_t} = \underset{(0.038)}{0.241^{***}}\ \mathrm{lPmdo_t} + \underset{(0.032)}{0.739^{***}}\ \mathrm{lPyft_t} + \widehat{\sigma}_t \tag{6}$$

Regime 2:

$$\mathrm{lPskj_t} = \underset{(0.025)}{0.052^{**}}\ \mathrm{lPmdo_t} + \underset{(0.021)}{0.932^{***}}\ \mathrm{lPyft_t} + \widehat{\sigma}_t \tag{7}$$

*,**,***, significant at 1%,5%,10% levels, st-error in brackets. $\widehat{\sigma}_t$ is the error term.

Clearly, the influence of the marine diesel oil price on the skipjack price is weaker during the second regime, the elasticity of price transmission decreasing from 24.1 to 5.2% while the fundamentals of the tuna market (catches and substitute species) are more present in Regime 2. Looking at Fig.4 gives an insight to the periods under Regime 1 (Regime 2 is easily deducted when the probability of Regime 1 is null). dominates:

Insert here Fig. 4 The two regimes of the relation between oil and skipjack tuna prices between January 2000 and September 2020

We can see that the two regimes alternate, although the higher probabilities of being in Regime 1 at each time step are rather found during the first decade, the second decade being more characterized by the second regime of price transmission, with a few exceptions around 2015 and 2019. We can therefore better understand the gaps between the actual and simulated price of skipjack shown in Fig. 2. The periods of Regime#1 of higher transmission between oil and tuna prices are rather found at the beginning of the sample period, i.e. prior to the financial crisis and when the economic growth rates were quite high. At the turn of the decade, landings stagnated for several years, creating shortages on the growing canned tuna market. After the crisis, the increasing spread between the two prices could therefore be explained by a more important role of landings upon the skipjack quotations. We can have a more specific understanding about the role of skipjack landings by looking at the parameters of the transition matrix:

$$\mathrm{P_t} = \begin{bmatrix} P_{11,t} & P_{12,t} \\ P_{21,t} & P_{22,t} \end{bmatrix} \tag{8}$$

From the results of the MS model (Table 4 in Appendix), the probabilities of transition between the two regimes can be written as a logistic function of lQskj:

$$\begin{cases} P_{11,t} = \frac{1}{1+e^{-0.216*lQskj_t}} \\ P_{21,t} = \frac{1}{1+e^{-(-0.284*lQskj_t)}} \end{cases} \tag{9}$$

Using the min and max values of Qskj in Table 1 helps to interpret the two transition probabilities of Eq.(9). In a month where the landings in Bangkok are low (15,164 tonnes), the probability of remaining in regime #1 is 89%, hence 11% of shifting to the second regime. Whenever the landings reach a maximum value (90,435 t), the likelihood of shifting to regime

#2 is 3 points lower. In other words, the high level of price transmission between the MDO price and the skipjack price is more likely to occur when the tuna market is not under the stress of low landings and when the tension is rather on the oil market. However, in case of shortage on the tuna market and if the tension on the oil market is relaxed, the role of tuna landings prevail and oil is no longer a dominating driver of tuna prices.

5 Discussion of the results

The relationship between the oil price and the price of food commodities might be overlooked by economists although most food industrial processes are fossil fuel-based, particularly in fisheries [Parker and Tyedmers (2015), Parker et al. (2015)]. The fuel use intensity of an industrial purse-seine fleet is estimated around 500 Litres per tonne of caught fish, but it can reach nearly 700 Litres in some cases and varies according to the fishing technique [Chassot et al. (2021), Basurko et al. (2022)]. Consequently, marine diesel oil represents a substantial share of costs, between 20 and 30% of total fishing costs for high-seas fleets, although the tuna purse-seine fleet is considered more efficient than others in terms of energy return on investment indicator, and even when it is compared to many agricultural production activities (Guillen et al., 2016).

We hypothesized that such an important energy input should be somehow visible in the price of skipjack tuna which is valued around USD1280 per tonne at the Bangkok market (sample mean between 2000 and 2020), major international marketplace in the world by the volume of trade (nearly $600,000$mt were imported by Thailand in 2019). A strong relationship would allow to predict future tuna prices, helping both fishing and canning companies to plan their economic results and investment. On this particular expectation, our first results from a price transmission model applied to the relationship between marine diesel oil and skipjack tuna prices between January 2000 and September 2020 were quite disapointing because no cointegration relation could be found. However, searching for structural breaks with different econometric procedures [Lavielle (2005), Bai and Perron (2003), Gregory and Hansen (1996)] allowed to identify at least two possible breakpoints in July 2004 and September 2010. The first date concerned mainly the oil market. The period starting in 2004 has been characterized by a sharp increase of crude oil prices. Between July 2004 and July 2008, the average USD price per barrel has grown by 258% because of the tremendous demand from fast growing economies like China and south-East Asian countries, thus creating supply shortages, locally and globally (Casamassima et al., 2009). This could explain the first breakpoint found in the *Pmdo* series, followed by several other successive changes marking the booms and busts of the worldwide conjuncture.

The second date was more interesting because it could potentially affect the two time series and their relation. As far as the cannery-grade tuna market is concerned, the global catches stagnated for several years between 2007 and 2012 around 2.5 million tonnes after a continuous increase over the past decades (the average annual growth rate of landings being +5% since 1950 according to the FAO FishstatJ data). During this 6-year period, the demand kept on increasing at the steady rate of $+3-4\%$, corresponding to the average growth rate of frozen skipjack imports since 1976, thus creating a shortage effect on the market and higher prices. The monthly growth rate of skipjack prices over the dataset sample (Jan. 2000-Sep. 2020) being less than 1% on average, it grew by nearly +4% between February 2007 and August 2008, when the financial crisis stopped the upward trend. The twofold shock of stable catches and the economic downturn of the late 2000s has deeply affected the long- run equilibrium between oil and tuna prices. A structural change model (Gregory and Hansen, 1996) indicated that both intercept (i.e. the spread or margin) and slope (the elasticity of price transmission) were modified after the break. The spread has increased after the 2010 breakpoint but, more importantly, the elasticity of price transmission has been reduced from 0.516 to 0.316 between the two periods, meaning that the pass-through of oil prices to skipjack tuna prices has been degraded. Whenever the oil price increases by 10%, the tuna price only increases by 3% in the last decade, instead of +5% a decade ago. Other influences had to be searched for.

This was done through the introduction of a substitute price (i.e. the leading price of another tuna species sold on the same market, yellowfin tuna or *T. albacares*), and the monthly quantity of skipjack imports in Thailand, in a Markov-switching model. With this approach, a clear regime shift appeared significant throughout the two decades: the quality of price transmission between oil and tuna prices alternates between phases of high and low pass-through. In particular, prior to the financial crisis or so, the first regime of high transmission between the two markets prevails, while the second regime of lower transmission dominates the past decade. In the meantime, the oil market has experienced a high volatility period with spectacular ups and downs and the tuna market, after decades of steady growth, is increasingly stretched by an imbalance between the increasing worldwide demand and tuna catches reaching a ceiling after a long period of expansion [Miyake et al. (2010), Dueri et al. (2016), Mullon et al. (2017), Scherrer and Galbraith (2020)]. In the estimated model outcome, we reported a regime shift at the turn of the 2010s: a first regime where the tuna price responds quite well to the oil market shocks, and a second regime where other variables related to the tuna market become more influential. Interestingly, the likelihood of Regime #1 (better pass-through between Pmdo and Pskj) is related to higher quantities sold on the tuna market, whereas the relationship between the two markets is affected by the market pressure of low landings or higher demand for fish. This result is similar to those found in other studies about the contrasted influence of an oil price increase according to the phase of the economic cycle [Raymond and Rich (1997), Yahya et al. (2019), Dahl et al. (2020)]. In the first cited study, using a Markov-switching model, the authors showed that an increase of oil prices during the boom periods had little impact on the economy, but tends to affect more deeply the results during slow- growing phases. Yahya, Oglend and Dahl (2019, 2020) found similar results with wavelet and copula methods applied to the crude oil price connected to agricultural prices on Futures markets: the spillover and dependence parameter between energy and ten agricultural markets decline during period of economic prosperity and spike during economic turmoil periods such as the 2008 global financial crisis (Dahl et al., 2020). In a closer case study to our own results, Asche et al. (2013) also found two Markov discrete regimes in the relationship between the fishmeal and the soybean markets, both supplying aquaculture and terrestrial animals feed markets. Their interpretation is the following one: whenever the fishmeal market faces a shortage because of a climatic event like a strong El Niño Southern Oscillation, then the two markets are disconnected with a more volatile and higher relative price of fishmeal (Asche et al., 2013). In this regard, structural breaks or regime shifts observed in commodity markets can help signalling more global changes such as environmental events (Smith et al., 2017).

What lessons can be drawn from this study? It is clear that the years and decades to come will see higher tensions on the oil market, ending the flourishing expansion of the high-seas purse- seine fleet targeting tropical tuna species since the early 1950s, and which is highly energy-consuming [Parker and Tyedmers (2015), Tickler et al. (2018), Sala et al. (2018), Chassot et al. (2021), Basurko et al. (2022)]. The most predictable scenarios for oceanic fisheries of large pelagic are darker with respect to global changes [Maury et al. (2017), Scherrer and Galbraith (2020), Bell et al. (2021)], and the food requirements of the growing population will put pressure on the tuna market, thus creating a squeeze between a declining supply and an increasing demand (Mullon et al., 2017). The regime#2 of the MS model is more likely to be the new standard, relaxing the influence of oil rates on tuna prices and moving back to the fundamentals of the market (GDP per capita and price of substitutes). Consequently, we recommend tuna traders not to use the oil price on Futures markets as a reliable predictor of tuna prices in the short and mid-terms for their hedging operations [Dillon and Barrett (2016), Su et al. (2019)]. However, energy remains a powerful driver of the industry, as shown by the long-term relationship between the oil and tuna prices, and as such modellers must integrate this fact in their predictive models of global food demand scenarios for the 21^{st} century [Bodirsky et al. (2015), Flies et al. (2018)].

Notes

[1]Such as the Shared Socioeconomic Pathways (SSP) scenarios proposed by the Intergovernmental Panel on Climate Change (IPCC).

[2]Data source: FFA Fisheries Development Division.

[3]www.customs.go.th/Customs-Eng/Statistic/ StatisticIndex2550.jsp under the HS code 0303.43.0000 (frozen skipjack as cannery-grade tuna). Data series collected by the FFA Fisheries Development Division.

[4]www.bunkerworld.com/prices/port/sg/sin/

[5]www.eia.gov. ($lPmdo = 0.972 \times lPnyhfo$)

[6]The ADF test values of the unit root test for lmdo were -2.08 and -1.82 with C and with C+T, resp. The ADF stat in first difference was -10.77^{***} and the KPSS test value was 5.178^{***}. The series is therefore I(1). For lpskj, the ADF values in levels were -2.65^{*} and -3.09, respectively, but the ADF-GLS (-0.478) and KPSS (2.71^{***}) concluded that the series was also I(1) DS.

[7]The dates were confirmed by a Bai-Perron test procedure under the BIC and RSS criteria (Bai, 1997),(Bai and Perron, 2003)

[8]The cointegration equation had the following form: $lPskj - 1.2748 \times lPyft^{***} + 2.2704^{***}$.

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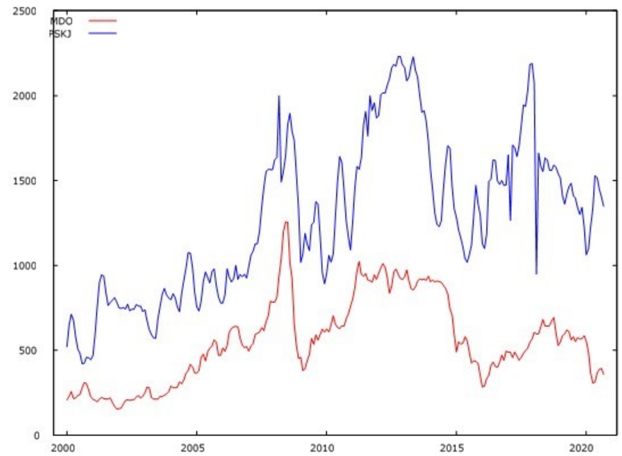

Figure 1: Prices of skipjack in Bangkok and MDO in Singapore (USD/t)
Source: FFA Fisheries Development Division

Table 1: Main statistics

Stat	Pmdo	Pskj	Pyft	Qskj
Min	154.3	419.7	691.0	15,164
1st Qu.	357.1	899.9	1210.5	33,691
Median	536.5	1263.0	1615.0	43,701
Mean	552.8	1278.3	1604.5	43,839
s.d.	252.4	463.7	464.8	13,895
3rd Qu.	693.3	1590.4	1922.5	54,460
Max	1256.0	2230.0	2607.0	90,435

Source: FFA Disheries Development Division and https://www.customs.go.th/
Monthly prices are in USD per tonne and the monthly quantity Qskj is in tonnes

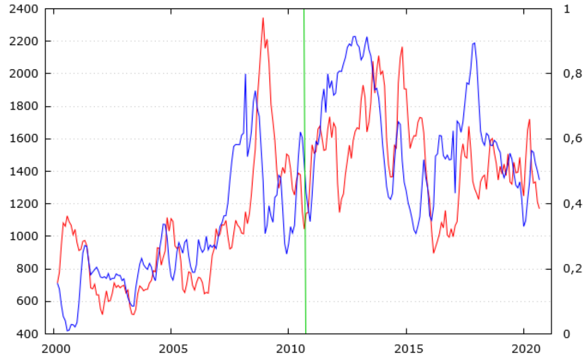

Figure 2: Prediction of the skipjack price (in USD/t)
(blue line = actual price, red line = simulated price from the VECM since April 2000, green vertical line = structural break of September 2010, right axis)

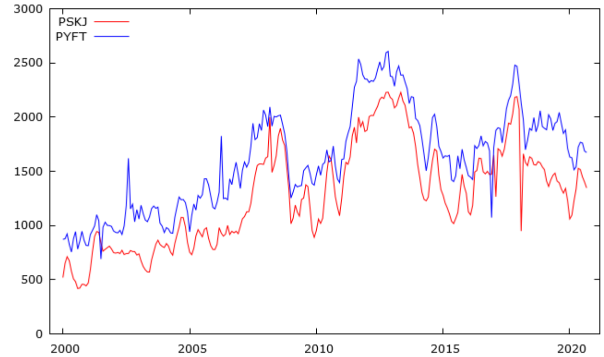

Figure 3: The price of skipjack and yellowfin tuna in the Bangkok market (USD/t)

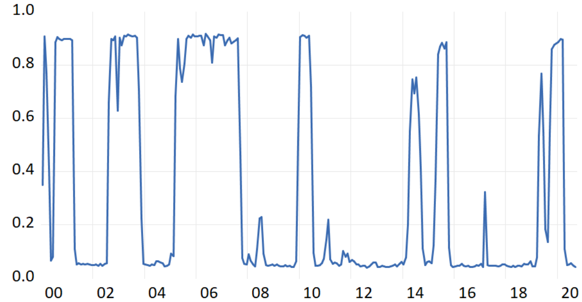

Figure 4: Markov Switching one-step ahead predicted regime probabilities P(State(t)= regime 1)

Appendix

Results of the Markov-Switching regression between oil and tuna prices

Dependent Variable: LPSKIPJACK
Method: Markov Switching Regression (BFGS / Marquardt steps)
Date: 05/20/21 Time: 21:06
Sample: 2000M01 2020M09
Included observations: 249
Number of states: 2
Initial probabilities obtained from ergodic solution
Standard errors & covariance computed using observed Hessian
Random search: 25 starting values with 10 iterations using 1 standard deviation (rng=kn, seed=580457119)
Convergence achieved after 23 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Regime 1				
LOG(MDO)	0.241069	0.038357	6.284869	0.0000
LOG(YELLOWFIN)	0.739069	0.032514	22.73069	0.0000
Regime 2				
LOG(MDO)	0.052374	0.024987	2.096044	0.0361
LOG(YELLOWFIN)	0.932706	0.021053	44.30302	0.0000
Common				
LOG(SIGMA)	-2.379025	0.049723	-47.84553	0.0000
Transition Matrix Parameters				
P11-LOG(QSKJ)	0.216463	0.039000	5.550301	0.0000
P21-LOG(QSKJ)	-0.283649	0.037856	-7.492770	0.0000

Mean dependent var	7.084354	S.D. dependent var	0.392267
S.E. of regression	0.110254	Sum squared resid	2.966060
Durbin-Watson stat	0.947304	Log likelihood	198.0649
Akaike info criterion	-1.534658	Schwarz criterion	-1.435773
Hannan-Quinn criter.	-1.494855		

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