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Guillotreau Patrice, Frédéric Lantz, Lesya Nadzon, Jonathan Rault, Olivier
Maury

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1 Price transmission between energy and fish markets:
2 are oil rates good predictors of tuna prices?

3
4 July 5, 2022

5 *Short title: Price transmission between oil and fish markets*

6
7 **Abstract**

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

20 1 Introduction

21 In a world of uncertainty characterized by significant environmental, economic and geopolit-
22 ical changes, forecasting commodity prices remains a difficult though stimulating and neces-
23 sary challenge for economists [Asche et al. (2016), Gordon (2020)]. Most food processes in the
24 21st century use energy-intensive technologies and bunker costs represent a major expense in
25 fish supply chains. This is the case for high-seas fishing targeting tuna species [Parker et al.
26 (2015), Basurko et al. (2022)]. We should logically observe a high degree of transmission
27 between oil rates and tuna prices (Yahya et al., 2019).

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

38

39 Economic knowledge about tuna markets improves gradually [Herrick Jr and Squires (1989),
40 Squires et al. (2006), Jeon et al. (2008), Guillotreau et al. (2017), Sun et al. (2019)], but is
41 still far from being sufficient to accurately forecast the future prices of tuna several months,
42 years or even decades ahead. In particular, the linkage between the energy sector and the
43 fishing industry is overlooked in the existing literature, with a few rare exceptions [Tyedmers
44 and Parker (2012), Parker and Tyedmers (2015), Guillen et al. (2016)]. However, the existing
45 literature deals more with the energy returns of fishing than about the relationship between
46 the cost of energy and the price of fish. This latter question is nonetheless important to

47 understand the economic drivers of the fishing effort and their impact on the dynamics of
48 global fisheries. In particular, long-run scenarios need to rely on simple but robust economic
49 models to test for the long-term consequences of severe impacts affecting social and ecological
50 systems [Dueri et al. (2016), Maury et al. (2017), Mullon et al. (2017), Bell et al. (2021)]. For
51 example, if lower catches cannot fully supply the growing market demand any longer, prices
52 may increase proportionally, so as to leave the fishers' income unchanged (Sun et al., 2017)?
53 Conversely, if the catch becomes lower with constant prices, an increasing energy cost may
54 deter fishers to maintain the same level of effort, hence relaxing the pressure on stocks. On a
55 more theoretical ground, the relationship between the oil and fish markets is also interesting
56 because the optimal exploitation rules of an exhaustible and renewable resource are differ-
57 ent. The Hotelling rule applied to the optimal exploitation of exhaustible resources equalizes
58 the growth rate of prices to the discount rate, under a finite time horizon. For a renewable
59 resource like wild fish, the marginal productivity of stocks added to a marginal stock effect
60 on the fishing rent must be equal to the discount rate at the optimum level of exploitation
61 over an infinite time horizon. Any increase of the discount rate can have opposite effects
62 on extraction rates, accelerating the exhaustion of oil reserves but preserving the renewable
63 stocks at a higher level of biomass, hence resulting in higher catches and lower fish prices
64 (Hannesson, 1986). Fish markets, whose demand is often found price-elastic, would therefore
65 face a fast-growing price of oil energy beyond the peak oil, thus creating a potential price
66 squeeze that would affect the profit margins of the fishing industry.

67 Despite the intensive use of energy in many food production processes, research works ana-
68 lyzing the link between both markets are not very common [Yahya et al. (2019), Dahl et al.
69 (2020)]. This is why our research contributes to the empirical literature by analyzing the
70 co-evolution of energy and fish prices. In particular, we selected a procedure combining var-
71 ious time series techniques to determine possible break dates in the two markets separately,
72 and in their relationship. Because the efforts of analysts attempting to predict the price of
73 commodities several months ahead are rather concentrated on the oil market, the idea is to
74 test for the long-run relationship between the price of Marine Diesel Oil (MDO) and the price
75 of skipjack (*Katsuwonus pelamis*). If a long-run relationship can be found between the two

76 markets, and according to the direction of the Granger causality, we could be in a position
77 to predict confidently the evolution of the skipjack price from the oil Futures market. More
78 precisely, by looking at the relationship between both markets, we hope to learn whether
79 any actual influence of the oil price on the skipjack price is passing through the supply-side
80 (energy being a major component of the marginal cost of fishing) or the demand-side for
81 these two global natural resources [Mullon et al. (2017), Maury et al. (2017)]. The oil market
82 being global, just like the market for canned tuna through which skipjack is mostly traded,
83 the dynamics of both prices might well be linked to the worldwide demand growth, just like
84 many other food commodities [Yahya et al. (2019), Dahl et al. (2020)].

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

94

95 **2 Literature survey**

96 An increasing number of research works attempts to model the global food demand scenarios
97 for the 21st century [Valin et al. (2014), Bodirsky et al. (2015), Flies et al. (2018)]. In
98 particular, the authors try to do so in order to assess the consequences of reference climate
99 scenarios¹ on food production and consumption levels. Food models are influenced by many
100 different drivers such as real income and prices, but also trade policy changes, population
101 growth and characteristics, the diet patterns, urbanization, and of course by the availability
102 of commodities on the supply side (Valin et al., 2014). This is all the more true when it
103 concerns wild and common resources such as fishery products. Climate change is expected

104 to transform profoundly the level of biomass and the spatial distribution of fish populations,
105 justifying the interest of modelling global demand for fishery products to better understand
106 its long-run drivers [Maury et al. (2017), Scherrer and Galbraith (2020), Mullon et al. (2017),
107 Bell et al. (2021)].

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

118 Beyond the interest of understanding food demand drivers, the modelling efforts concerning
119 the demand for wild-caught fish show the interest of unveiling the flexibility coefficients
120 which represent key market-incentives for fishery management. The effort reduction which is
121 required to adjust the fishing capacity to the sustainable level is more likely to be accepted
122 if the price response allows fishers to earn more by catching less and conversely [Sun et al.
123 (2017), Sun et al. (2019)]. Tuna fisheries offer a perfect illustration of a global commodity
124 being harvested in the three oceans, supplying the canning industry with large quantity of
125 raw materials, and being traded as a major source of fish proteins in many countries around
126 the world [Miyake et al. (2010), Mullon et al. (2017)]. The market is global and all regional
127 markets are now quite well integrated under the leading role of the Bangkok market [Jiménez-
128 Toribio et al. (2010), Sun et al. (2017)]. This market presents the valuable advantage of its
129 central position between two oceans and its vicinity to the most productive fishing grounds
130 in the world (Miyake et al., 2010).

131 Like for any other ocean-wide fishery, tuna fishing and trade are highly dependent on energy-
132 consuming industrial fleets, particularly because of an increasing distance from ports to

133 fishing grounds (Tickler et al., 2018). The conventional index assessing the high level of
134 catch dependence to energy is the Fuel Use Intensity (FUI) measuring the ratio of consumed
135 oil Litres per tonne of landed fish. Across a great number of species and world regions, the
136 mean FUI found by Parker and Tyedmers (2015) since 1990 was $706 L * t^{-1}$. A study reported
137 an average FUI value of $368 L * t^{-1}$ for the global purse-seine fleet targeting skipjack and
138 yellowfin tuna (Parker et al., 2015). Two more recent and accurate research works based on
139 vessel data looked at the FUI of the European purse-seine fleet fishing tuna in the Indian
140 Ocean showed a variable FUI value, oscillating between 390 and $680 L * t^{-1}$ since 2015
141 according to the level of catches, fishing effort (quantitatively and qualitatively) and vessel
142 size [Chassot et al. (2021), Basurko et al. (2022)]. Keeping in mind an average marine diesel
143 oil price of $\$554 t^{-1}$ between January 2018 and October 2020 and a conversion factor of 0.72
144 kg per Litre, the fuel cost would reach nearly $\$200$ per tonne of fish with a $500L * t^{-1}$ FUI.
145 The average price of frozen skipjack being $\$1468$ per tonne for the same period², the energy
146 cost would represent 14% of the ex-vessel price of frozen tuna. Bunker costs are undoubtedly
147 an important component of expenses for purse-seiners targeting skipjack tuna. The share of
148 energy costs is estimated between 20% and 30% of operating costs, depending on the level
149 of oil rates (Miyake et al., 2010). This proportion could even rise up to 50% (Parker and
150 Tyedmers, 2015) or more in case of extremely high prices on the oil market as it happened
151 in September 2008 when the crude oil barrel skyrocketed at $\$147$ per barrel, just before the
152 financial crash (Tyedmers and Parker, 2012).

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

162 only allowed standard additive of gasoline, thus creating a dependence between the oil price
163 and the ethanol (hence corn) price.

164 However, using Partial Equilibrium frameworks may overlook the macroeconomic effects of
165 oil prices on food markets. Using a global CGE model, some authors have shown that energy
166 prices have also an impact on real income and trade balances (Gohin and Chantret, 2010).
167 The effect would be positive for crude-oil producing countries, but negative for oil importing
168 countries. The authors simulated a 20% reduction shock in world oil reserves and found
169 evidence of a negative relationship between world food and energy prices, countervailing
170 the cost-push effect of an oil price change to food prices. However, one could turn the
171 macroeconomic effect upside down and also hypothesize that an increasing oil price is the
172 result of global economic growth which could somehow benefit to food prices in general, and
173 fish prices in particular. Whatever the channel of pass-through from oil prices to skipjack tuna
174 prices, either as a marginal cost-push mechanism, or a demand-pull process affecting both oil
175 and fish markets, we believe that the relationship deserves a thorough analysis through time
176 series and through a variety of empirical models based on cointegration theory (Johansen,
177 1988). First of all, a positive correlation and causality found between oil rates and fish prices,
178 if ever demonstrated, could be used to forecast the tuna price as input for canneries with the
179 underlying support of Futures oil market contracts, as proved in other global fish markets
180 like the salmon market (Asche et al., 2016). Secondly, a long-term linkage between oil prices
181 and tuna prices may also be an interesting contribution to a more prospective analysis of
182 global food demand with respect to the peak oil and climate-driven scenarios. What can be
183 the future of the large-scale tuna fisheries if high fishing costs and price elasticity of final
184 demand hamper the profitability of purse-seine vessels and canneries (Sala et al., 2018)?
185 Thirdly, if the relationship appears not to be robust enough in the long term, it might reveal
186 some structural changes and regime shifts that could be meaningful to better understand the
187 price formation on the global tuna markets. Besides the influential status of oil for many
188 food commodities, what is the role of landings or substitute species in the fishery markets,
189 keeping in mind that the world is facing a maximum supply of 80 or 90 million tonnes of
190 wild-caught fish for more than three decades, this supply being now threatened by the global

191 warming process going on and the lack of stringent regulation (Scherrer and Galbraith, 2020).
192 In parallel, the world population is still growing with a higher level of income per capita
193 and requires an increasing amount and diversity of food proteins. What we propose in this
194 research is to reconcile the partial and general equilibrium hypotheses about the link between
195 energy and fish markets by applying a parsimonious cointegration model of price transmission
196 between the oil and fish markets. To that end, we adopt an original procedure combining
197 various structural break searching techniques. First, we check the existence of a long-term
198 equilibrium relation between the marine diesel oil price and the skipjack tuna price. Secondly,
199 we look for structural break dates in the two markets separately, and then jointly by different
200 econometric means. By doing so, we expect more robust outcomes and confidence about the
201 identification of break dates. Thirdly, we investigate the supply or demand-sided nature of
202 the long-term relationship between the two prices by considering other factors affecting the
203 tuna market.

204 **3 Relationship between the prices of skipjack and marine** 205 **diesel oil**

206 **3.1 Data**

207 The monthly price of skipjack (Pskj) is extracted from the FFA Fisheries Development Di-
208 vision using the Thaiandese customs database from January 2000 to September 2020 (249
209 obs.)³. The price of Marine Diesel Oil (Pmdo) in Singapore is also supplied by the FFA
210 Fisheries Development Division with data published by Bunkerworld⁴ from January 2000
211 to May 2018. Between June 2018 and September 2020, the series is complemented by the
212 estimated price obtained from a robust long- term relationship existing between the MDO
213 in Singapore the New York Harbor No. 2 Heating Oil Future Contract ⁴⁵. Both series are
214 transformed by their logarithm to test for the quality of price transmission in the long run
215 (Fig. 1 and Table 1). Table 1 is complemented by the descriptive statistics of two other time
216 series (the price of yellowfin tuna (*Thunnus albacares*) -Pyft- and the quantity of skipjack
217 imports in Thailand -Qskj- measured in metric tonnes, that will be used later in the study to

218 enrich the price transmission model). These two series are extracted from the same database
219 of Thaiandese customs.

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

221 Insert here Table 1 Main statistics

222 First of all, we check that all series are I(1), in particular for Pmdo and Pskj. This is the case
223 from ADF, ADF-GLS and KPSS tests⁶. Seasonal unit roots needed also to be scrutinized in
224 the following equation suggested by Miron (1996):

$$y_t - y_{t-1} = \mu_1 D_1 + \mu_2 D_2 + \dots + \mu_{12} D_{12} + \epsilon_t \quad (1)$$

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

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

241 3.2 Looking for structural breaks

242 Long time (monthly) series running throughout several decades can be affected by disrupting
243 events, as observed in other fish markets [Asche et al. (2013), Smith et al. (2017)]. Conse-
244 quently, we suspected the relationship between the price of skipjack and that of MDO to
245 have been modified during the sampled period. To search for structural breaks, we first used
246 the Lavielle segmentation procedure based on the maximum likelihood criteria with the R-
247 package `segclust2d` [Lavielle (2005), Patin et al. (2019)]. With a L_{min} of 24 months (minimum
248 length of a segment) and $K_{max} = 7$ (maximum number of breaks), we tested the two series
249 separately. For the oil price, the optimal number of breaks was 3, hence 4 segments (break-
250 points: July 2004, December 2010 and November 2014). For the price of Skipjack alone, only
251 one break was found in February 2007⁷. However, the break dates did not match between
252 the two series. A joint segmentation was then performed with the two series simultaneously
253 and gave one single breakpoint (i.e. 2 segments) in July 2004. According to the International
254 Energy Agency, demand for oil grew at its strongest pace in almost three decades in 2004,
255 mainly driven by supply bottleneck and strong economic growth in Asia and America. The
256 market was also tense because of uncertainty about the security of oil supplies during the
257 second Gulf war (ECB monthly Bulletin, May 2005).

258 The cointegration equation including a break in July 2004 was then successfully tested with a
259 price transmission elasticity of 0.41, and an increasing intercept after July 2004 ($R^2 = 0.64$).
260 This is in line with the result obtained on a truncated sample of the same monthly data (from
261 2000:02 to 2015:02) by (Nadzon, 2016), who found an elasticity of 0.64 and a $R^2 = 0.73$ with
262 a Fully-Modified Least Square method (Nadzon, 2016). However, the structural change could
263 also concerned a shift in the slope of the relation. A Gregory-Hansen test was therefore per-
264 formed to look for the right specification (Gregory and Hansen, 1996). Such models allow to
265 determine when the unknown breakpoints occur (looking at the stationarity of the residuals
266 through the minimum value of the ADF statistic corresponding to the date), and if the lat-
267 ter affects the constant, the trend or the slope in the regression model, thus explaining the
268 absence of cointegration. Their model (4) was selected as the best one, with a shift in both
269 the constant and the slope with no trend (Gregory and Hansen, 1996):

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

270

271 The ADF test procedure gave a breakpoint in September 2010 ($t - stat = -5.171$ with
 272 $AR\ lag = 2$), while the Phillips procedure pointed at a breakpoint in March 2007 with
 273 $z_t = -4.986$ and $z_a = -45.343$. Including either break date in the model, the two series
 274 became cointegrated. However, the Gregory-Hansen model (4) showed no significant param-
 275 eter estimates for the break of March 2007 on the constant term or the slope, unlike the
 276 break of September 2010. Consequently, only the first breakpoint of the ADF procedure (i.e.
 277 September 2010) was considered and tested in the following cointegration model:

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

278

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

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

$$\Delta \text{Lpskj}_t = -\underset{(-4.697)}{0.118} \widehat{\mu}_{t-1} + \underset{(6.141)}{0.361} \Delta \text{Lpskj}_{t-1} + u_t$$

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

(t-stat in brackets)

290

291

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

300

301 3.3 A weak prediction of the skipjack price

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

310

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

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

$$\begin{aligned}
 lPskj_t = & \frac{0.172}{(0.692)} + \frac{0.877}{(20.860)} lPskj_{t-1}^{***} + \frac{0.034}{(1.620)} lPmdo_{t-1} + \frac{0.045}{(2.217)} lQskj_{t-1}^{**} \\
 & + \frac{0.036}{(1.671)} \times I(t > 129)^* + u_t \quad (5)
 \end{aligned}$$

328 $T = 248 \quad \bar{R}^2 = 0.93 \quad F(1, 243) = 4.919 \quad \hat{\sigma} = 0.101$

329 *, **, ***, significant at 1%, 5%, 10% levels, t-stat in brackets.

330 After the introduction of the lagged quantity variable, the oil price became non-significant,
 331 as if the Bangkok tuna price was responding more to the past level of landings than to the
 332 oil input price. Unfortunately, the own-price flexibility coefficient did not show the expected
 333 sign, i.e. normally negative and unitary as found in previous studies (Sun et al., 2017),
 334 presumably because of an identification problem. The level of catch and landings is also
 335 possibly affected by the oil rate itself, because the $lQskj$ equation of the VAR system had a
 336 very significant parameter estimate for the lagged $lPmdo$ variable. The level of landings could

337 certainly be affected by the energy cost of fishing beyond a threshold, but there may be some
338 other explanation behind the degraded correlation after the breakpoint and the alternate
339 periods of good and bad connections between the two markets. This needed to be scrutinised
340 with potential regime shifts between some sub-periods. In a preliminary conclusion, we
341 consider that the oil price, although influential for the skipjack price, is not a good predictor
342 of skipjack prices for every period.

343 4 Introducing a regime shift in the oil-tuna price relation

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

352

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

354

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

360 Confirming the results of the 2010 study, which was based on a sample between January 1995
361 and December 2006 (Jiménez-Toribio et al., 2010), a cointegration relation was easily found
362 between the two I(1) series of the logarithmic prices of skipjack and yellowfin⁸. A VECM
363 model proved the weak exogeneity of the yellowfin price, the skipjack price reverting back

364 to its long- run relationship with the price of the other species (with a speed of adjustment
 365 of -0.1317 , significant at the 1% level) while the former one is significant but positive, thus
 366 not moving back to the long-run relation. We also assumed that the transition probabili-
 367 ties between the two regimes are depending on the skipjack landings, since the quantity of
 368 skipjack, which is prevailing in the Bangkok market (Sun et al., 2017), showed some kind of
 369 influence over the skipjack price in the previous VAR equation.

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

372 Regime 1:

$$IPskj_t = \underset{(0.038)}{0.241^{***}} IPmdo_t + \underset{(0.032)}{0.739^{***}} IPyft_t + \hat{\sigma}_t \quad (6)$$

373 Regime 2:

$$IPskj_t = \underset{(0.025)}{0.052^{**}} IPmdo_t + \underset{(0.021)}{0.932^{***}} IPyft_t + \hat{\sigma}_t \quad (7)$$

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

375

376

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

382

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

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

$$P_t = \begin{bmatrix} P_{11,t} & P_{12,t} \\ P_{21,t} & P_{22,t} \end{bmatrix} \quad (8)$$

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

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

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

406 #2 is 3 points lower. In other words, the high level of price transmission between the MDO
407 price and the skipjack price is more likely to occur when the tuna market is not under the
408 stress of low landings and when the tension is rather on the oil market. However, in case of
409 shortage on the tuna market and if the tension on the oil market is relaxed, the role of tuna
410 landings prevail and oil is no longer a dominating driver of tuna prices.

411 5 Discussion of the results

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

422 We hypothesized that such an important energy input should be somehow visible in the price
423 of skipjack tuna which is valued around USD1280 per tonne at the Bangkok market (sample
424 mean between 2000 and 2020), major international marketplace in the world by the volume
425 of trade (nearly 600,000mt were imported by Thailand in 2019). A strong relationship would
426 allow to predict future tuna prices, helping both fishing and canning companies to plan their
427 economic results and investment. On this particular expectation, our first results from a
428 price transmission model applied to the relationship between marine diesel oil and skipjack
429 tuna prices between January 2000 and September 2020 were quite disappointing because no
430 cointegration relation could be found. However, searching for structural breaks with different
431 econometric procedures [Lavielle (2005), Bai and Perron (2003), Gregory and Hansen (1996)]
432 allowed to identify at least two possible breakpoints in July 2004 and September 2010. The
433 first date concerned mainly the oil market. The period starting in 2004 has been characterized

434 by a sharp increase of crude oil prices. Between July 2004 and July 2008, the average USD
435 price per barrel has grown by 258% because of the tremendous demand from fast growing
436 economies like China and south-East Asian countries, thus creating supply shortages, locally
437 and globally (Casamassima et al., 2009). This could explain the first breakpoint found in
438 the *Pmdo* series, followed by several other successive changes marking the booms and busts
439 of the worldwide conjuncture.

440 The second date was more interesting because it could potentially affect the two time
441 series and their relation. As far as the cannery-grade tuna market is concerned, the global
442 catches stagnated for several years between 2007 and 2012 around 2.5 million tonnes after a
443 continuous increase over the past decades (the average annual growth rate of landings being
444 +5% since 1950 according to the FAO FishstatJ data). During this 6-year period, the demand
445 kept on increasing at the steady rate of +3–4%, corresponding to the average growth rate of
446 frozen skipjack imports since 1976, thus creating a shortage effect on the market and higher
447 prices. The monthly growth rate of skipjack prices over the dataset sample (Jan. 2000-Sep.
448 2020) being less than 1% on average, it grew by nearly +4% between February 2007 and
449 August 2008, when the financial crisis stopped the upward trend. The twofold shock of
450 stable catches and the economic downturn of the late 2000s has deeply affected the long- run
451 equilibrium between oil and tuna prices. A structural change model (Gregory and Hansen,
452 1996) indicated that both intercept (i.e. the spread or margin) and slope (the elasticity
453 of price transmission) were modified after the break. The spread has increased after the
454 2010 breakpoint but, more importantly, the elasticity of price transmission has been reduced
455 from 0.516 to 0.316 between the two periods, meaning that the pass-through of oil prices to
456 skipjack tuna prices has been degraded. Whenever the oil price increases by 10%, the tuna
457 price only increases by 3% in the last decade, instead of +5% a decade ago. Other influences
458 had to be searched for.

459 This was done through the introduction of a substitute price (i.e. the leading price of another
460 tuna species sold on the same market, yellowfin tuna or *T. albacares*), and the monthly
461 quantity of skipjack imports in Thailand, in a Markov-switching model. With this approach,
462 a clear regime shift appeared significant throughout the two decades: the quality of price

463 transmission between oil and tuna prices alternates between phases of high and low pass-
464 through. In particular, prior to the financial crisis or so, the first regime of high transmission
465 between the two markets prevails, while the second regime of lower transmission dominates
466 the past decade. In the meantime, the oil market has experienced a high volatility period
467 with spectacular ups and downs and the tuna market, after decades of steady growth, is
468 increasingly stretched by an imbalance between the increasing worldwide demand and tuna
469 catches reaching a ceiling after a long period of expansion [Miyake et al. (2010), Dueri et al.
470 (2016), Mullon et al. (2017), Scherrer and Galbraith (2020)]. In the estimated model outcome,
471 we reported a regime shift at the turn of the 2010s: a first regime where the tuna price
472 responds quite well to the oil market shocks, and a second regime where other variables
473 related to the tuna market become more influential. Interestingly, the likelihood of Regime
474 #1 (better pass-through between P_{mdo} and P_{skj}) is related to higher quantities sold on the
475 tuna market, whereas the relationship between the two markets is affected by the market
476 pressure of low landings or higher demand for fish. This result is similar to those found in
477 other studies about the contrasted influence of an oil price increase according to the phase of
478 the economic cycle [Raymond and Rich (1997), Yahya et al. (2019), Dahl et al. (2020)]. In
479 the first cited study, using a Markov-switching model, the authors showed that an increase of
480 oil prices during the boom periods had little impact on the economy, but tends to affect more
481 deeply the results during slow- growing phases. Yahya, Oglend and Dahl (2019, 2020) found
482 similar results with wavelet and copula methods applied to the crude oil price connected
483 to agricultural prices on Futures markets: the spillover and dependence parameter between
484 energy and ten agricultural markets decline during period of economic prosperity and spike
485 during economic turmoil periods such as the 2008 global financial crisis (Dahl et al., 2020).
486 In a closer case study to our own results, Asche et al. (2013) also found two Markov discrete
487 regimes in the relationship between the fishmeal and the soybean markets, both supplying
488 aquaculture and terrestrial animals feed markets. Their interpretation is the following one:
489 whenever the fishmeal market faces a shortage because of a climatic event like a strong El
490 Niño Southern Oscillation, then the two markets are disconnected with a more volatile and
491 higher relative price of fishmeal (Asche et al., 2013). In this regard, structural breaks or
492 regime shifts observed in commodity markets can help signalling more global changes such

493 as environmental events (Smith et al., 2017).

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

511 Notes

512 ¹Such as the Shared Socioeconomic Pathways (SSP) scenarios proposed by the Inter-
513 governmental Panel on Climate Change (IPCC).
514

515 ²Data source: FFA Fisheries Development Division.

516 ³www.customs.go.th/Customs-Eng/Statistic/StatisticIndex2550.jsp under the HS code
517 0303.43.0000 (frozen skipjack as cannery-grade tuna). Data series collected by the FFA
518 Fisheries Development Division.

519 ⁴www.bunkerworld.com/prices/port/sg/sin/

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

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

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

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

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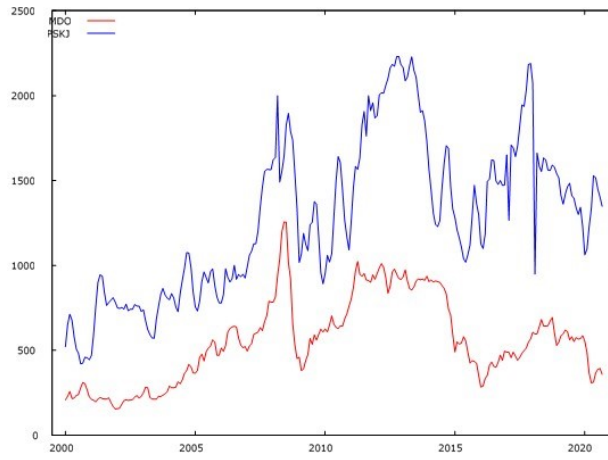


Figure 1: Prices of skipjack in Bangkok and MDO in Singapore (USD/t)
Source: FFA Fisheries Development Division

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

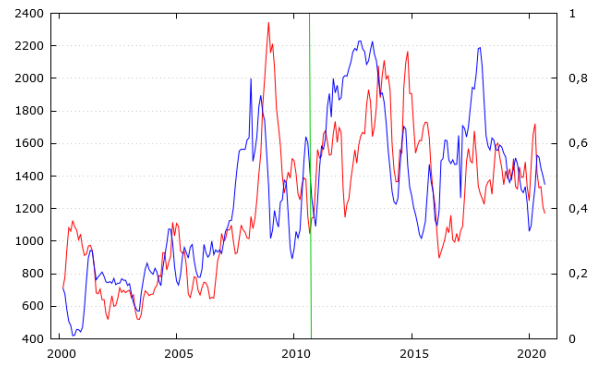


Figure 2: Prediction of the skipjack price (in USD/t)
(blue line = actual price, red line = simulated price from the VECM since April 2000, green vertical line = structural break of September 2010, right axis)

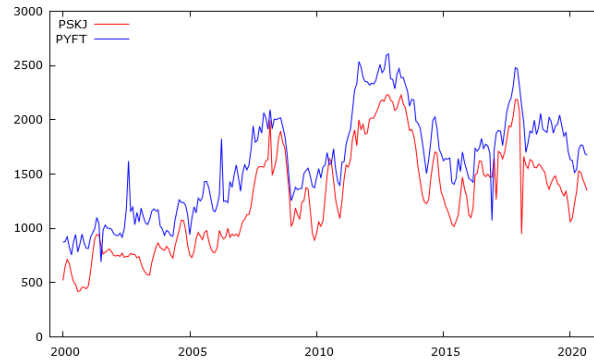


Figure 3: The price of skipjack and yellowfin tuna in the Bangkok market (USD/t)

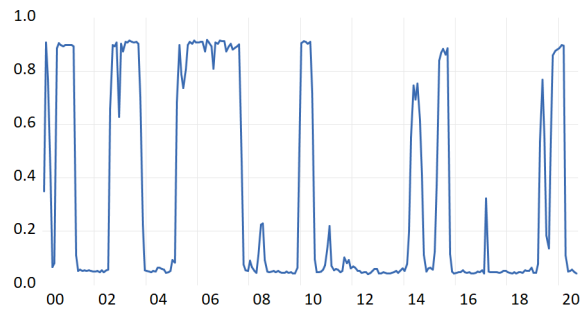


Figure 4: Markov Switching one-step ahead predicted regime probabilities $P(\text{State}(t)= \text{regime 1})$

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			