Does *cantrang* trawl fishing become more efficient after the partial trawl ban? a case study of technical efficiency of *cantrang* fishery in the Java Sea – Indonesia

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Abstract. *Cantrang*- a modified Danish seine that targets demersal fish and squid in the Java Sea- has been banned partially in all Indonesian waters since 2015. The policy goal was to limit the ecological impact by reducing the number of the fleet. This study compares the technical efficiency (*T.E.*) of *cantrang* fishing before and after the ban and identifies input technology that affects fleet efficiency. A *Data Envelopment Analysis* (*DEA*) was used to calculate the *Technical Efficiency* of the *cantrang*. In this case, the *T.E*. measures the ability of *cantrang* to maximize catch using a given set of production inputs such as Goss Tonnage (G.T.), fishing duration, and the number of skippers using the time series daily landing data from 2007 to 2017. The results show pure and scale efficiency of the fleet increases considerabıy during the after-ban period compared to the before-ban period. This relatively high technical efficiency at post-ban occurred due to the meaningful reduction of fishing days while optimizing the number of onboard skippers per vessel. Although the portion of skippers per vessel increases substantially at post-ban, this growth minimizes the onboard fish-shorting, packaging, and grading works. Therefore, these tasks can be done faster than before.

1 Introduction

Indonesia is the second-largest marine capture producer globally [1]. Based on science recommendations, the total standing stock was 12,541,438 tons in 2017 [2]. In 1978, the Danish seine-like trawl fishing method known locally as *cantrang* was firstly introduced to the Java Sea. The *cantrang* fishing in the Java Sea contributed about 30% of the total national marine capture landings [3]. Since its inception, *cantrang* has become the famous fishing gear that significantly contributes to Indonesian marine capture production [4].

The main targets of *cantrang* fishing are mostly high-value commercial fish such as squid and threadfin bream. However, some low-value demersal fishes such as goatfish and purple-spotted bigeye were also targeted to fulfill the demand of fish paste industries. According to

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the Ministry of Marine Affairs and Fisheries (MMAF) of Indonesia statistical data, the total standing stock of demersal and reef fish in the Java Sea is 687.476 tons with an estimated potential/target yield of around 549981 tons in 2017 [2].

Even though *cantrang* fishing has contributed to most of the demersal fish landings in the northern Java Sea, the government, through the MMAF, ruled a ban on trawlers fishing including *cantrang* fishing in the Java Sea in 2015. The ministry has seen *cantrang* as a harmful fishing method because it usually takes small fish and causes seabed damage. Although the regulation was enacted in 2015, the latest formal directive from the ministry in 2016 still allows some *cantrang* vessels to fish as long as they pass the G.T size re-measurement task and change their fishing gears to a 'millennium gillnet'. However, this shifting fishing gear scheme is not very successful. The ministry only allows fishing to those vessels with an active permit but is restricted to issuing a new license.

Since the partial fishing ban was implemented in 2015, information about the vessels' performance, particularly their technical efficiency, is limited. This research is aimed to estimate pure and scale efficiency performances of all *cantrang* ships that are still fishing over the eleven years from 2007 to 2017 and compare the results among the period of pre-ban and post-ban.

2 Materials and Methods

2.1. Description of the Data

We used secondary data of daily landing data of *cantrang* vessels between January 2007 and June 2017, consisting of 12.536 observations. The data were gathered by the trained enumerator hired by the local fishery office of Tegal Port in Central Java Province with geo-position of site location. In the Tegal port, the owners or assigned persons from each vessel that loaded their harvest must report directly to the officer in Tegal Port right after the loading process is finished. Figure 1 below illustrates the fishing location of the *cantrang* vessels that covers all areas of the Java Sea.

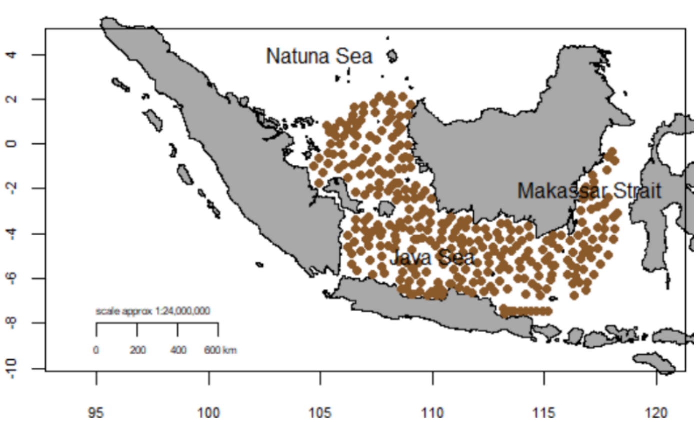

Fig. 1. Plotting fishing spots of *cantrang* in the Java Sea during 2007 – 2017

2.2. Data Analysis

The Data Envelopment Analysis (DEA) was carried out [5] to benchmark the *cantrang*'s vessel efficiency and compare them before and after the ban. A fishing fleet is much efficient if it yields a higher output (maximum catch) but utilizes the minimum amount of inputs such as size of the vessel (Gross Tonnage/G.T.), number of trips, and number of the onboard crew when compared to a reference vessel. This study uses the total catch of the boat as an output. Therefore, the T.E. of a *cantrang* vessel can be written as:

$$Technical\ efficiency = \frac{Actual\ productivity}{Reference\ productivity\ (estimated\ frontier)} \tag{1}$$

DEA approach is known as a non-parametric frontier that is based on linear modeling. The DMUs (Decision-Making Units) inputs and outputs (in this case, DMUs is the *cantrang* vessel) can be used to estimate a virtual frontier that is the best in each vessel category, knowing as the technical efficiency values.

We apply a set of the input variables to define what variables (trip length, number of crews, and G.T. size) fishers have been adjusted to optimize their total catch. DEA's two essential concepts are constant-return-to-scale (CRS) and variable-return-to-scale (VRS). The input-oriented constant return-to-scale model (DEA-CCR) is proposed by [6], while [7] presented the variable-return-to-scale model (DEA-BCC). An input-oriented DEA-CCR and DEA-BCC have expressed as the below linear modeling envelopment problems with different constraints [5]:

$$min_{\phi,\sigma}\ \phi \tag{2}$$

$$s.t. \quad \phi x_s - x\sigma \geq 0 \tag{3}$$

$$y_\sigma \geq y_s \tag{4}$$

$$\sigma \geq 0 \qquad (DEA\ CCR) \tag{5}$$

$$e\sigma = 1 \qquad (DEA\ BCC) \tag{6}$$

The DEA-BCC represents pure technical efficiency. On the other hand, the DEA-CCR expresses the whole *TE*, which resulting two apparatuses: scale and pure *TE*. Once the calculation shows DEA-CCR and DEA-BCC models have different efficiency score, meaning that the particular DMU has scale inefficiency (S.E), so the S.E. of the s-th observed boat could be calculated as follow:

$$SEs = \frac{CCRs}{BCCs} \tag{7}$$

A “Benchmarking” package in open source R software has been used for the analysis. The details on the methodology can be found in [7] and [8].

3 Results

3.1 Technical efficiency benchmarking

We assume technical efficiency in this study is defined as a maximization of the vessels' output given a set of inputs such as the number of trips, the number of onboard crews, and the G.T. size over the amount of catch as the linear model. Table 2 shows the *T.E.* performance of all vessels measured in this study for DEA-CCR, and DEA-BCC as well as scale efficiencies. As shown in Table 2, overall *TE* of DEA-BCC score (CCR, mean = 0.29) can be divided into pure *TE* score (BCC, mean = 0.59) and scale efficiency means score 0.55.

Figure 2 presents an individual scale efficiency score of all vessels that were fluctuated during the year 2007 to 2017. In this study, scale efficiency means the ability of each *cantrang* plate to operate as close to its most productive scale size as possible**.** In 2007, most vessels had high-scale efficiency scores compared to the following year, 2008 to 2011. However, their scores then increased slightly in 2012 and 2013, before dropping back in 2014, a year before the ban implementation.

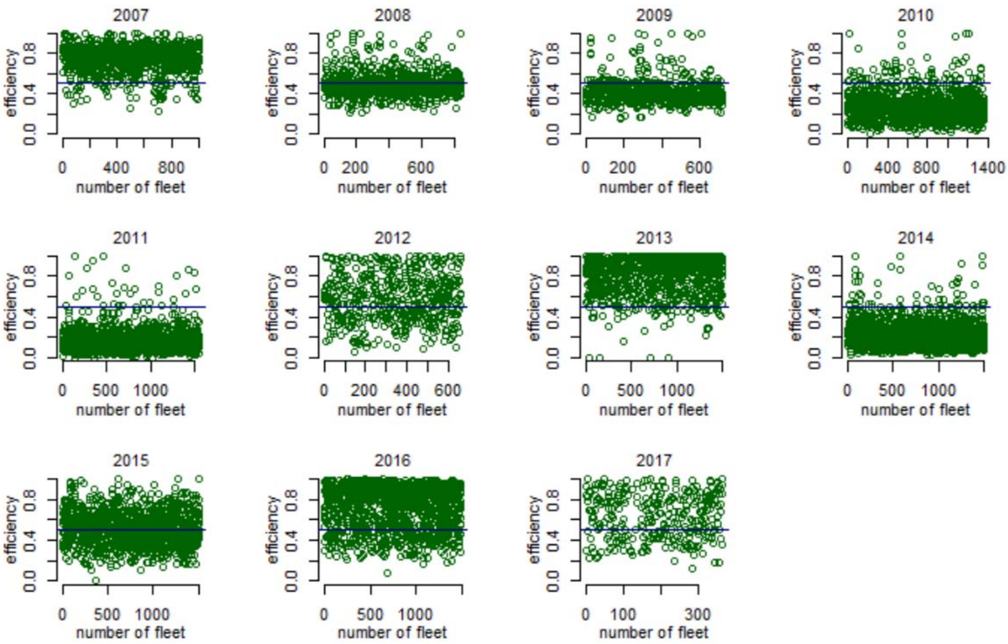

Fig. 2. The scale efficiency performance of the *cantrang* vessel over the eleven years from 2007 to 2017

Interestingly, during the trawl ban implementation in 2015, most *cantrang* vessels performed well, showing a gradual increase of the scale efficiency scores in the following years, 2016 to 2017.

Table 1 shows the pure technical efficiency (DEA-BCC) of the vessels, showing the portion of boats that have a high efficient score (0.9<=E<=1) increased during the post-ban from 20015 to 2017. In 2015, a year after the ban was imposed, the proportion of most-efficient vessels increased more than double, from 1.7% to 4.1% in 2014 and 2015, then gradually increased in the following years, 5.8% and 9.3% in 2016 and 2017, respectively.

Table 1. Percentage of efficient distribution of the *cantrang* vessel from 2007 to 2017.

Year	**DEA BCC efficiency range (%)**					**Total (%)**
	0.1<= E <0.3	**0.3<= E <0.5**	**0.5<= E <0.7**	**0.7<= E <0.9**	**0.9<= E <=1**	
2007	1.0	0.8	54.3	39.5	4.4	100
2008	0.0	0.5	37.5	48.1	14.0	100
2009	0.0	0.0	32.7	66.2	1.1	100
2010	0.1	18.2	53.8	26.6	1.3	100

Year	DEA BCC efficiency range (%)					Total (%)
	0.1<= E <0.3	0.3<= E <0.5	0.5<= E <0.7	0.7<= E <0.9	0.9<= E <=1	
2011	0.0	1.7	42.1	53.8	2.4	100
2012	78.3	11.8	5.2	2.1	2.7	100
2013	83.8	13.0	1.3	0.9	1.0	100
2014	37.5	48.4	9.4	3.0	1.7	100
2015	0.0	12.3	61.9	21.7	4.1	100
2016	0.0	11.7	63.9	18.6	5.8	100
2017	0.0	18.1	61.3	11.3	9.3	100

Table 1 above also shows a significant proportion (37.5% – 83.8%) of vessels that have low pure efficiency scores (DEA-BCC) ranging from 0.1 to 0.3 (0.1<=E<0.3) were recorded from 2012 to 2014. On the other hand, a substantial proportion (61.3 to 63.9%) of vessels with relatively high-efficiency scores (0.5<=E<0.7) were occurred from 2015 to 2017, during the post-ban period.

Table 2. Technical efficiency (DEA-CCR, DEA-BCC, and Scale) of *cantrang* vessels during the pre-ban (2007 to 2014) and post-ban (2015 to 2017)

Year	DEA-CCR	DEA-BCC	Scale	Average
2007	0.52	0.71	0.74	0.61
2008	0.35	0.71	0.50	0.53
2009	0.32	0.75	0.43	0.53
2010	0.17	0.62	0.28	0.40
2011	0.12	0.70	0.17	0.41
2012	0.17	0.28	0.60	0.23
2013	0.16	0.27	0.80	0.19
2014	0.41	0.63	0.62	0.52
2015	0.32	0.63	0.51	0.48
2016	0.45	0.63	0.72	0.54
2017	0.41	0.63	0.64	0.52
Average	**0.29**	**0.59**	**0.55**	**0.43**

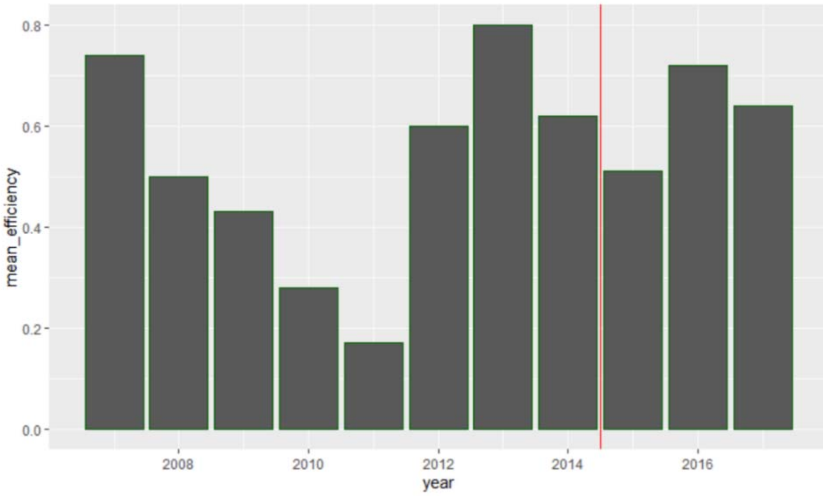

Fig. 3. The average scale efficiency of the *cantrang* vessel from 2007 - 2017

Unlike the pure efficiency (DEA BCC) scores in Table 1, Figure 3 represents the average scale efficiency scores of all *cantrang* vessels. The scores were decreased gradually from 2007 to 2011 but increased again from 2012 to 2017. The lower average scale efficiency score was in 2012 (scale efficiency = 0.17), while the highest was in 2013 (scale efficiency = 0.8).

4 Discussion

The results clearly show that the average scale efficiency scores were high in post-ban (2015 to 2017) compared to the period before the ban from 2007 to 2014, as shown in Figure 4 below. Table 3 shows that the average scale efficiency score was 0.615 at post-ban, significantly higher than 0.493 at pre-ban ($p < 0.05$). The high score of scale efficiency at post-ban indicates significant changes in input technology of the *cantrang* fishing vessel to maximize the catch as an output. As shown in Figure 5 below, there was a meaningful reduction in average fishing trip days of all ships during the post-ban period, from 71 fishing days in 2015 to be only 53 days in 2017. At the same time, a gradual increase in the number of onboard skippers was recorded over the eleven years from 2007 to 2017 (Figure 5). Unlike the current study, the average technical efficiency score of the ocean prawn trawl fishery in Australia was relatively higher, ranging between 0.3 to 0.98, with the mean score of all vessels equal to 0.9 [9].

During the post-ban, most cantrang vessels reduced their fishing days but accommodated more crews from ships that stopped fishing, so the number of crew per vessel increased considerably. This strategy could help the boat to reduce the ship from the expensive cost of fuel consumption. However, it could increase the productivity of the boat since many crews mean the fishing process, such as fish sorting and onboard packaging, is faster. The improvement of technical efficiency in fishing vessels is a function of progress in the fishing skill of vessel crews, as skippers learn more about where to find and catch fish, or skippers shift toward larger vessels eventually increase the fishing capacity [10].

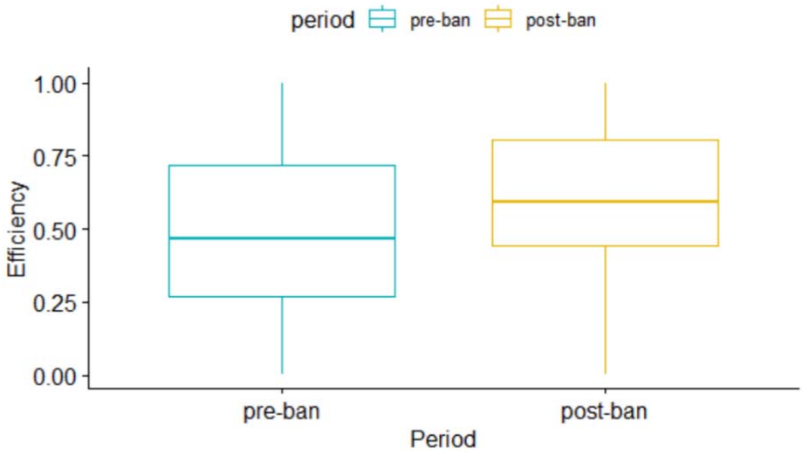

Fig. 4. Boxplot of scale efficiency of the *cantrang* vessel during the period of pre-ban and post-ban

Table 3. Summary stats of pre-ban and post-ban scale efficiency

Period	Count	Mean	Standard Deviation
post-ban	2838	0.615	0.2139
pre-ban	8235	0.493	0.2691

Since 2010, many boat owners have equipped their vessels with an onboard freezer to maximize the capacity of the vessels. A slight gradual increase in the G.T. size over the year 2012 to 2017 (Figure 5) might be related to the installment of this onboard freezer, as an input technology, over the eleven years. This increased vessel capacity could accommodate more catch and optimize the increased number of crews per vessel. The boat owners could maximize the work time of teams in fishing shift systems and reduce the sorting, grading, and packaging process that are the most time-consuming tasks. With an onboard freezer, the quality of the fish can also be maintained at a better grade until the vessel landed then unloads to the port. A ship equipped with onboard frozen storage can fish longer at sea and store fish during the periods of fishing season and high catching rates. These advantages could maintain a better quality of the harvested fish [11].

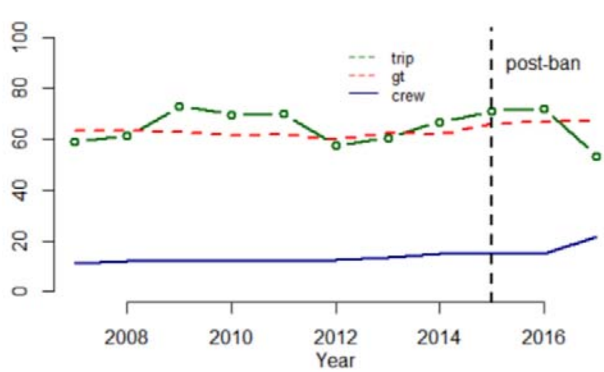

Fig. 5. The number of trips, onboard crew, and G.T. size from 2007 to 2017

5 Conclusion

The pure and scale efficiency of the *cantrang* fleet increased substantially at the after-ban period, compared to scores of pure and scale efficiency at the pre-ban period. The majority of the vessels improved their ability to operate as close to their most productive scale size as possible at post-ban, as indicated by a significant scale efficiency score during that period. Furthermore, by reducing the length of the trip and optimizing the number of crew per vessel, the majority of the *cantrang* represent better efficiency performance right after the ban was imposed.

6 Acknowledgment

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Appendix 1.

Table 4. Summary statistics of all variables

Variables	2007 (N = 1007)				2008 (N = 845)				2009 (N = 722)			
	Mean (SD)	Median	Minimum	Maximum	Mean (SD)	Median	Minimum	Maximum	Mean (SD)	Median	Minimum	Maximum
Catch	6,890 (1600)	7,100	1,650	14,000	9,730 (1960)	9,930	4,350	34,800	10,500 (2150)	10,400	2,950	50,500
Number of Trips (day)	59.0 (46.4)	42	7	279	61.2 (45.6)	45	7	333	72.9 (58.5)	50	6	317
Number of Crew	11.2 (1.77)	12	5	22	12.2 (1.75)	12	7	29	12.3 (1.14)	12	3	19
Gross Tonnage (G.T.)	63.2 (24.5)	48	4	119	63.5 (24.5)	48	4	119	62.7 (23.7)	47	4	119

Variables	2010 (N=1367)				2011 (N=1557)				2012 (N=664)			
	Mean (SD)	Median	Minimum	Maximum	Mean (SD)	Median	Minimum	Maximum	Mean (SD)	Median	Minimum	Maximum
Catch	12,100 (6810)	11,300	500	101,000	13,600 (9510)	11,900	160	125,000	14,400 (6190)	14,100	1,590	44,000
Number of Trips (day)	69.5 (57.4)	46	6	332	70.1 (61.9)	44	6	338	57.6 (55.6)	37	5	199
Number of Crew	12.2 (1.58)	12	8	20	12.3 (1.76)	12	8	21	12.8 (2.38)	12	7	27
Gross Tonnage (G.T.)	61.4 (25.3)	47	4	119	62.0 (26.2)	47	4	119	59.8 (26.3)	47	3	119

Variables	2013 (N=1504)				2014 (N=1503)				2015 (N=1514)			
	Mean (SD)	Median	Minimum	Maximum	Mean (SD)	Median	Minimum	Maximum	Mean (SD)	Median	Minimum	Maximum
Catch	15,800 (5760)	15,300	2,900	94,700	15,700 (5490)	15,300	2,560	74,100	18,300 (6580)	17,700	150	89,900
Number of Trips (day)	60.6 (55.7)	40	1	346	66.8 (53.9)	48	6	321	71.1 (53.9)	56	13	334
Number of Crew	13.7 (2.56)	13	1	20	14.9 (2.87)	15	7	30	15.2 (3.26)	15	8	30
Gross Tonnage (G.T.)	62.5 (25.3)	55	4	117	62.1 (27.7)	47	4	118	66.3 (28.5)	64	4	118

Variables	2016 (N=1487)				2017 (N=366)			
	Mean (S.D.)	Median	Minimum	Maximum	Mean (S.D.)	Median	Minimum	Maximum
Catch	12,200 (4150)	12,500	1,600	26,200	11,000 (4290)	10,400	1,900	23,300
Number of Trips (day)	72.1 (58.4)	60	12	317	53.3 (25.2)	51	18	156
Number of Crew	15.1 (2.92)	15	8	27	21.7 (3.46)	22	12	27
Gross Tonnage (G.T.)	66.6 (29.0)	66	4	118	67.5 (29.1)	66	4	117