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Adaptive response of beam trawl fishers to rising fuel cost

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In this paper, we develop models to test different hypotheses on the optimal towing speed at which fuel savings are traded off against the reduction in catch due to the decrease in swept area. The model predicts that optimal towing speed is a decreasing function of fuel price and an increasing function of fish abundance and price. The model was fitted to vessel monitoring system (VMS) data. By means of mixture analysis, these VMS data were attributed to one of three behavioural modes: floating, towing, or navigating. Data attributed to the towing mode were used to determine the model that best fit the data. The preferred model includes a maximum towing speed and a component describing the decline in catch efficiency with decreasing towing speed. Towing speed is reduced by up to 14%. The savings obtained by reducing towing speed were estimated for each month and showed that vessels reduced their fuel consumption by between 0 and 40%.

Keywords: fishing fleets, fuel consumption, fuel price, towing speed.

Introduction

Since the introduction of steam and diesel propulsion in the 20th century, engine power and fuel consumption in fisheries have steadily increased (Engelhard, 2008). Trawl fisheries in particular are characterized by high fuel costs (Berkes and Kislalioglu, 1989; Ziegler and Hansson, 2003; Schau *et al.*, 2009). In the last decade, global fisheries used almost 50 billion litres of fuel while landing just over 80 Mt of marine fish and invertebrates (Tyedmers *et al.*, 2005). Impacts of higher fuel prices are large for fisheries compared with other industries because fuel costs relative to revenue are large (Waters and Seung, 2010). When catch rates and fish prices cannot compensate for increasing fuel costs, the economic viability of fisheries is jeopardized. High costs force less efficient vessels out of business. However, subsidies to compensate fishers for increased fuel costs have often served to negate this effect (Sumaila *et al.*, 2008). Nevertheless, in some fisheries, oil crises have indeed resulted in a decrease in the overall number of vessels (Rijnsdorp *et al.*, 2008). Since 2005, oil prices have increased, reaching levels similar to those experienced at the peaks in the 1970s and 1980s.

Increasing fuel prices potentially result in investment in energy-saving technologies or switching to less energy-demanding fishing methods. For example, the introduction of the "twin trawl" in otter trawling fisheries has reduced net drag in the water, while maintaining a horizontal net opening (Sainsbury, 1971). Likewise, innovations such as changes in hull shape and propulsion systems have resulted in fuel savings of 10–20% in Norwegian fisheries (Schau *et al.*, 2009). These adaptations require capital investments and may not be realized immediately. Options for immediate adaptation to increasing fuel prices are possible through changes in fishing behaviour. Fishers may compensate increasing costs by longer working hours and fewer men per vessel (Mitchell and Cleveland, 1993), or they may fish closer to port (Sampson, 1991; Bastardie *et al.*, 2010). Another behavioural response to increasing fuel prices is to reduce towing or navigation speed. Since fuel consumption increases exponentially with vessel speed (Ronen, 1982; Corbett *et al.*, 2009), any reduction in speed while either fishing or navigating to the fishing grounds may reduce cost (Abernethy *et al.*, 2010). Beare and Machiels (2012) observed that, between 2003 and 2010, changes in average towing speed of the Dutch beam trawl fleet were related to changes in oil price.

In this paper, we build on the study of Beare and Machiels (2012) by exploring how changes in fuel price affect the optimal towing speed of individual vessels. We develop a mathematical model of optimal towing speed based on a number of processes involved in cost and benefits of fishing, with increasing complexity. The basic model includes the effect of towing speed on fishing costs (fuel consumption) and benefits (catch). The more complex models include (i) a maximum vessel speed related to vessel engine power; and (ii) a non-linear relationship between catch efficiency and towing speed as indicated from empirical studies (Rijnsdorp et al., 2008). These models are fit to observations of fuel price and towing speed for a number of vessels to test whether fishers optimize their towing speed. Observations stem from economic panel data and vessel monitoring system (VMS) data of the Dutch beam trawl fishery. The Dutch beam trawl fishery is a suitable candidate for the analyses because its high fuel costs make up $> 50\%$ of gross revenue (Taal et al., 2009; Abernethy et al., 2010). Finally, we test whether fishers, in addition to changes in towing and navigation speeds, have changed fishing grounds in response to changes in fuel price.

Material and methods

Vessel data were collected by the Dutch Ministry of Economics, Agriculture and Innovation (EL&I) responsible for fisheries. We compiled data for 13 vessels of ~ 1470 kW main engine power (range: 1467–1471 kW), which have been in operation for at least 6 years during the 2003–2010 study period using a traditional double-tickler chain beam trawl and for which catch, VMS, and economic data were available by trip (Table 1).

For each fishing trip, the weight of the landings by species, fishing area (ICES rectangle of $\sim 30 \times 30$ nm), date, and harbour at the start and end of the trip were extracted from official logbook data. Fishing vessel speed was estimated from the VMS database comprising observations ("pings") in 2 h intervals on the date, time, geographic location, vessel speed, and vessel direction (Hintzen et al., 2010). Erroneous VMS data were removed using the "vmstools" library in R (Hintzen et al., 2012). For the 13 vessels, there were $\sim 243\,000$ VMS ping data associated with fishing trips.

Economic data were collected by the Agricultural Research Economics Institute (LEI) in The Netherlands. These data are available for a panel of vessels that submit bookkeeping records to the LEI accounting department. Data include total value of the landings from sales slips, fuel consumption in volume by trip, and fuel price per litre paid at each refuelling.

Model

While at sea, a vessel can either (i) handle the gear while floating (shooting, hauling, repair); (ii) tow fishing gear; or (iii) navigate between the fishing grounds and a harbour (Rijnsdorp et al., 1998). Fishing cost is the summed cost of these three activity modes (Rijnsdorp et al., 1998; Sala et al., 2011): (i) the cost of handling the gear while floating, C_f; (ii) the cost of towing the gear, C_t; and (iii) the cost of navigating between harbour and fishing grounds, C_n. The monetary net revenue of a fishing trip U is determined by the cost of fishing and gross return R:

$$U = R - C_f - C_t - C_n. \tag{1}$$

The gross revenue is a function of time spent towing (T_t), catch efficiency (c), density of the resource in terms of its economic value (V), and towing speed S_t,

$$R = T_t c V S_t. \tag{2}$$

Here, catch efficiency is the fraction of fish being caught and retained in the net per unit trawled distance. For reasons of analytical tractability, we assume that the monetary costs of floating, C_f, are negligible and can be set to zero. This assumption seems justifiable because time spent floating is only a minor proportion of the total time at sea, and the engine is not used to propel the vessel while floating.

The monetary costs of towing and navigating depend on the time spent in each activity mode (T_t, T_n), on fuel coefficients β_t and β_n, on vessel speed for each activity mode (S_t, S_n), and on fuel price (P). Fuel coefficients determine the amount of fuel used per unit time as a function of vessel speed. During both towing and navigating, fuel consumption will increase with the cube of the speed (Ronen, 1982; Corbett et al., 2009):

$$C_t = T_t \beta_t s_t^3 P, \tag{3a}$$
$$C_n = T_n \beta_n s_n^3 P. \tag{3b}$$

Removing the C_f term from Equation (1) allows splitting the time spent at sea (T) into the proportion in which a vessel is towing (p_t) and the proportion in which a vessel is navigating (p_n). Then, substituting the other terms in Equation (1) with

Table 1. Overview of the number of trips per year and vessels in the sample with all available data.

Vessel no.	Engine power (kW)	Number of trips								
		2003	2004	2005	2006	2007	2008	2009	2010	Total
8	1471	0	35	36	41	40	41	38	0	231
10	1467	44	34	36	42	42	38	37	0	273
211	1469	36	34	33	36	37	41	38	0	255
214	1471	41	38	32	37	41	37	39	36	301
215	1467	23	35	33	20	4	2	32	31	180
226	1467	32	31	27	38	38	33	35	32	266
326	1470	36	40	37	33	29	31	33	0	239
355	1471	27	29	26	35	34	22	32	13	218
728	1471	8	8	3	9	2	1	24	0	55
942	1471	0	18	34	18	27	19	26	26	168
986	1469	15	5	1	31	31	34	13	0	130
1024	1471	24	28	37	26	25	25	6	0	171
1248	1471	36	35	36	40	34	44	35	35	295

Equations (2), (3a), and (3b) results in a monetary return rate:

$$\frac{U}{T} = p_t c V S_t - p_t \beta_t S_t^3 P - (1 - p_t) \beta_n S_n^3 P \tag{4}$$

The maximum monetary return rate as a function of towing speed S_t is given by the root of the first-order partial derivative of Equation (4) in the direction S_t. If we assume constant catch efficiency ($c = 1$), this results in the following equation for optimal towing speed:

$$S_t = \frac{\sqrt{V}}{\sqrt{3}\sqrt{\beta_t}\sqrt{P}} \tag{5}$$

Hence, optimal towing speed is a function of the inverse square root of fuel price (Figure 1). Further, optimal towing speed increases with resource density in terms of its economic value V and decreases with the coefficient of fuel consumption while towing β_t. Optimal towing speed is independent of trip duration and distance to the fishing ground.

The basic model resulting in Equation (5) implicitly assumes that vessels can increase towing speed indefinitely at low fuel prices. The first extension of the model is to assume that towing speed is constrained by maximum engine power. Hence, below a certain threshold fuel price, towing speed will be at a maximum H determined by engine power:

$$S_t = \min\left[\frac{\sqrt{V}}{\sqrt{3}\sqrt{\beta_t}\sqrt{P}}, H\right] \tag{6}$$

Lastly, the assumption of constant catch efficiency is relaxed. If catch efficiency c is a function of towing speed, the relationship between optimal towing speed and fuel price becomes more complex. Here, we assume that catch efficiency increases with towing speed following a sigmoid function $\frac{1}{1 + e^{(w - S_t)/a}}$ bounded by 0 and 1. In this relationship, w defines the midpoint of the sigmoid function, and a defines the slope. The relationship describes the escapement of fish from the approaching gear at low towing speeds that decreases at increasing towing speeds. The response function of gross revenue against towing speed then becomes:

$$R = T_t \frac{1}{1 + e^{(w - S_t)/a}} V S_t \tag{7}$$

The first-order partial derivative of the maximum utility rate in the direction S_t for this model follows from removing the C_f term from Equation (1), substituting the other terms with Equations (7), (3a), and (3b), and expressing the result as a utility rate:

$$\frac{U}{T} = p_t \left(\frac{V}{1 + e^{(w - S_t)/a}} + \frac{V S_t}{2a + 2a\cosh\left(\frac{w - S_t}{a}\right)} - 3 P S_t^2 \beta_t \right) \tag{8}$$

There is no analytical solution to the root of this equation with respect to S_t. Therefore, we use a Newton search algorithm to find the root for each set of parameters. From Equation (8), it is clear that p_t can be removed from the search algorithm. Examples of the shapes of the three functional forms of the predicted relationships from the increasingly complex models are plotted in Figure 1.

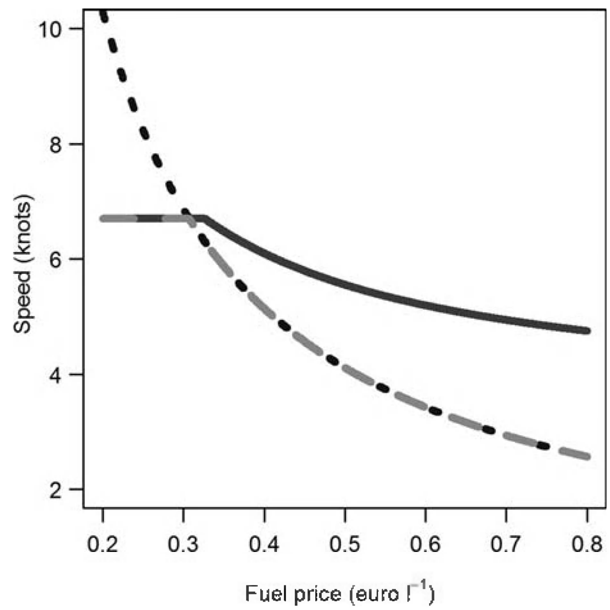

Figure 1. Three functional forms of the conceptual model: (i) basic model (dotted); (ii) threshold included (dashed); and (iii) catch efficiency effect of fishing speed included (drawn).

Vessel activity modes

The three activity modes are visible as three distinct peaks in the frequency distribution of the observed speeds in the VMS dataset (Fig. 2). Non-parametric mixture analysis was carried out to find component density functions describing the three behavioural modes. This was done for the VMS pings for each year and each vessel separately, using the expectation–maximization (EM) algorithm (Dempster *et al.*, 1977; McLachlan and Peel, 2000). The EM algorithm is implemented in the mixed distribution tool in R (Benaglia *et al.*, 2009a, b). The EM algorithm requires starting values for initial centres of the distributions, and these were chosen based on a visual inspection of a histogram of observed speeds of the entire dataset. Figure 2 gives an example of the frequency distribution of a single vessel in a single year combined with the estimated component density functions, as estimated by the mixed distribution tool.

The EM algorithm provides posterior probabilities of component inclusion for each VMS ping in each activity mode. For further analysis, each VMS ping is assigned to the activity mode with the highest posterior probability. A regression model is used to detect significant linear relationships between fishing and navigation speeds and fuel price for individual vessels.

For each trip, we estimated three indicators used for further analysis: (i) proportion of time spent in each mode; (ii) time spent in each mode; and (iii) mean of the cubed vessel speed in towing mode and in navigating mode. The proportion of time spent in each mode can be estimated by summing the number of pings assigned to each mode and dividing by the total number of pings. These proportions are denoted p_f for the proportion of time spent floating, p_t for the proportion spent towing, and

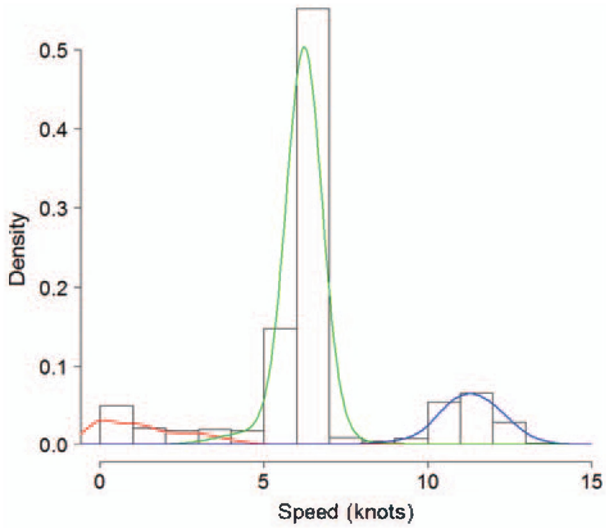

Figure 2. Frequency distribution of observed vessel speeds and the component density functions showing the activity modes during floating (red), towing (green), and navigation (blue). VMS records of a given speed were assigned to an activity mode based on the highest probability density.

p_n for the proportion spent navigating. Time spent in each mode is calculated by multiplying the proportions spent in each mode by total trip duration, as recorded in the official logbooks, and denoted T_f for time spent floating, T_t for time spent towing, and T_n for time spent navigating. The mean of the speeds is denoted $\overline{S_t}$ for towing and $\overline{S_n}$ for navigating. Likewise, the cubed speeds are denoted $\overline{S_t^3}$ for towing and $\overline{S_n^3}$ for navigating.

Before parameterizing and fitting the non-linear models described above, a simple linear model was fit to describe the relationship between vessel speed and fuel price. In this model, the slope and intercept of the relationship between vessel speed and fuel price was estimated from the data for all vessels, assuming a normally distributed error term. This analysis was done on towing speed and navigating speed independently.

Model parameterization

Statistical analysis of fuel consumption as a function of speed

Fuel consumption of a vessel depends on its activity mode. While floating, the speed of the vessel is determined by currents and winds acting on the vessel, and the rate of fuel use will be independent of vessel speed. During towing, the rate of fuel consumption is mainly determined by drag of the gear towed over the seabed and by drag of the vessel in the water. During navigation, the rate of fuel use is determined by drag of the vessel in the water. During both towing and navigating, the rate of fuel use will increase with the cube of navigation speed (Ronen, 1982; Corbett *et al.*, 2009).

Because the dataset contains fuel consumption per trip (F_t) and not per activity mode, we use the intertrip variation in time spent navigating or towing to estimate fuel consumption coefficients β_t and β_n for the two activity modes for each vessel independently. The two fuel consumptions coefficients are estimated in the linear model

$$F_t = \beta_t T_t \overline{S_t^3} + \beta_n T_n \overline{S_n^3} + \varepsilon, \qquad (10)$$

where ε is a normally distributed error term. We ignored fuel use during floating because time spent floating is a minor proportion of total time at sea (see Figure 2 and Table 2), and the engine is not used to propel the vessel while floating.

Table 2. Quartiles of key variables characterizing the trips of the vessels in the sample.

Variable	Parameter	First quartile	Median	Third quartile
Proportion floating	P_f	0.05	0.08	0.11
Proportion towing	P_t	0.79	0.84	0.88
Proportion navigating	P_n	0.04	0.07	0.11
Trip duration (h)	T	96	99	104
Trawled distance (miles)		485	543	594
Total distance (miles)		579	630	687
Fuel use per trip (litres)	F	32 292	36 055	39 329
Gross revenue per trip (Euro)	R	28 555	33 945	40 601

Catch efficiency – towing speed relationship

The only data available to estimate the effect of towing speed on catch efficiency are the catchability estimates obtained in the XSA stock assessment (Shepherd, 1999) carried out routinely for stock assessment purposes (ICES, 2011a). In the stock assessment for sole (*Solea solea*), time-series of catch per unit of effort data are used for the Dutch commercial beam trawl fleet (thousand million hp d^{-1}) and the ISIS Beam Trawl Survey (BTS) (numbers h^{-1}). After correcting for the differences in swept area between the two time-series, the data indicate that the ISIS BTS survey, which is towed at 4 knots, catches 46% of the number of age 3–9 sole caught by the commercial fleet fishing with a towing speed of ~ 7 knots. Since there are no data available to estimate the slope of the relationship, we assumed that the ogive would pass through 90% at a towing speed of 6 knots.

Fitting the models to observations

We follow the assumption that fishers are profit maximizers who modify their towing and navigation speeds in response to fuel cost within the constraints imposed by the vessel's engine power. Under this assumption, observations on the response of fishing speed of individual vessels to fuel prices should follow the model formulations described above.

The first model assumed that fishers maximize their profits by changing towing speed in relation to the increase in the price of fuel. The second model is a discontinuous extension of model 1 which estimates maximum towing speed that can be expected from the constraint set by the vessel's engine power. The third model extends model 2 by including a term that specifies how catch efficiency increases with increased towing speed.

The model fitting is done using a numerical maximum likelihood estimation. Data are assumed to be normally distributed, with means and standard deviations predicted by the model.

The negative of the log-likelihood function was minimized using evolutionary global optimization via the differential evolution algorithm (Price *et al.*, 2006). The evolutionary algorithm uses 500 vectors with parameter starting values chosen randomly from a uniform distribution. The algorithm then iteratively uses alteration and selection to minimize the objective function. Differential evolution is well suited to find the global optimum of a function of real-valued parameters, and does not require that the function is continuous or differentiable (Mullen *et al.*, 2011). After 500 iterations, the results were checked for convergence. Converged models are compared using the Akaike information criterion (AIC).

Distance to fishing ground

For each trip, the maximum distance to the arrival harbour is estimated by calculating the distance between each ping and the harbour, and selecting the ping with the largest distance. Changes in distance travelled to the fishing grounds per trip (nautical miles) relative to the price of fuel were studied using quantile regression (Koenker and D'Orey, 1987). Quantile regression estimates multiple rates of change (slopes) from the minimum to maximum response (Cade and Noon, 2003). Hence, it provides a complete picture of the relationship between distance travelled to the fishing grounds per trip (nautical miles) relative to the price of fuel by estimating this relationship for all quantiles of travelled distance.

All statistical analyses were done in R (version R 2.14.0; R Development Core Team, 2012), except the quantile regression that was done in SAS software v9.1 using the "quantreg" procedure.

Results

Vessel activity modes

The mixture analysis for three component density functions of speed for each year and each vessel separately resulted in 106 estimates of VMS speed distribution mixtures. Each VMS ping was assigned to the mode with the highest posterior probability, revealing that vessels spend ~8% of their time floating, 84% of their time fishing, and 7% of their time navigating (Table 2). Mean speed of pings associated with floating was 1.3 knots, median speed associated with fishing was 6.6 knots, and median speed associated with navigating was 11.9 knots. Median trip duration of the selected vessels in the study period was 99 h, and the median distance travelled during a trip was 630 nautical miles. The median amount of fuel used was 36 000 l trip^{-1}.

Changes in towing and navigation speeds

Median towing and navigation speeds have decreased in the period 2003–2010 (Figure 3b and c). The decrease agreed with the increase in fuel prices paid by the vessels (Figure 4a) that followed world crude oil prices. Revenue rate during the study period showed a clear seasonal cycle, with peak revenues in autumn and winter and low revenues in spring and summer (Figure 4b).

Linear regression of average speeds as a function of oil price reveals that there are significantly different responses for different vessels in the sample (Table 3). For the towing mode, slope is significantly different ($\alpha = 0.05$) from zero for ten of the 13 vessels (Table 4). For these significant relationships, slope in towing speed ranged between −0.328 and −1.496. For the navigation mode, slope is significantly different ($\alpha = 0.05$) from zero for 11 vessels. Slope in navigation speed ranged between −0.78 and −3.914, suggesting that the response in navigation speed was stronger than in towing speed.

Model fit

The optimization model was parameterized by estimating the relationship between fuel consumption and vessel speed for the towing and navigation activity modes for each vessel. Fuel consumption coefficients were found to be significantly different for different vessels. The fuel consumption coefficient for towing ranged from 1.09 to 1.55, with standard errors ranging from 0.02 to 0.06 (Figure 5). Coefficients for navigation speed were less well estimated, ranging from 0.12 to 0.33, with standard errors ranging from 0.03 to 0.12. The higher standard errors are probably due to the relatively low percentage of time spent navigating. Fuel consumption during towing was, therefore, more than fourfold higher than during navigation at equal speeds. Fuel consumption at median towing (6.6 knots) and navigation

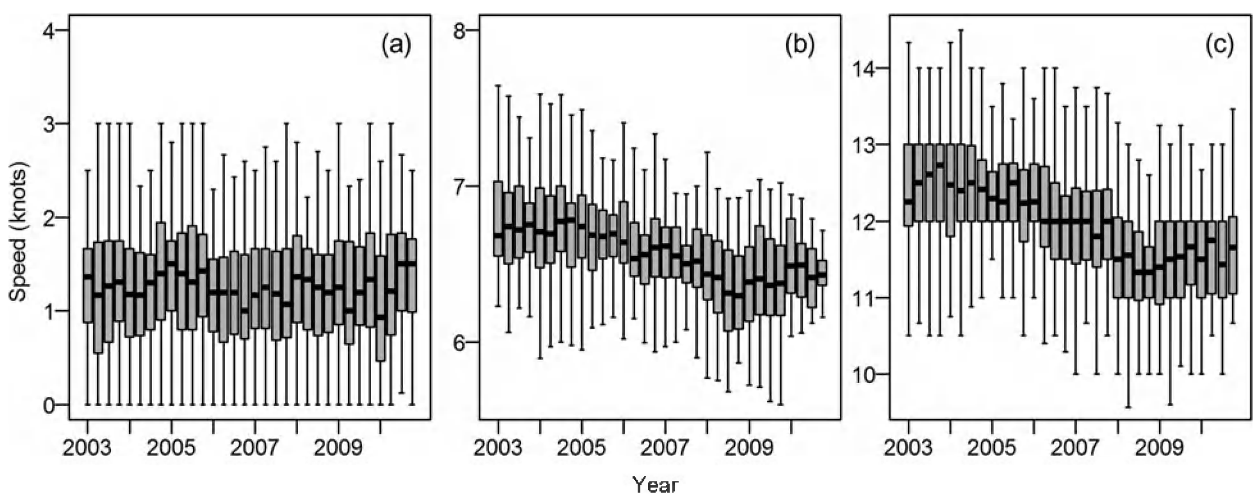

Figure 3. Box plot of vessel speeds during the three activity modes per trip over time for the three behavioural modes: (a) floating; (b) towing; and (c) steaming. Each box represents the estimates for a quarter of the year. The horizontal line represents the median, the hinges indicate the first and third quartiles, and the whiskers extend to the data points away from the box by no more than 1.5 box lengths.

(11.9 knots) speeds were ~ 400 l h^{-1}. Other parameter settings were based on the observed characteristics concerning trip duration, revenue rate, and distance travelled (Table 2).

The base model—with towing speed being a function of the inverse square root of fuel price—has 14 estimable parameters: one for each of the 13 vessels in the sample and one for the standard deviation in the likelihood function. After 500 iterations, improvement in the likelihood estimate of the differential evolution algorithm had ceased. The associated parameter estimates result in a poor fit of the model to the data (Figure 6). At low fuel price, predicted towing speed is higher than observed, whereas at higher fuel price, predicted towing speed is well below observations. Apparently, the model structure does not fit the observations well. Including a maximum towing speed in the model reflects the effect of maximum engine power limiting maximum speed. Compared with the base model, this model adds 13 free parameters: one maximum speed for each vessel. The fit of the model to the data increases substantially, reflected in the increase in log likelihood from −3875.6 to 281.1. The AIC for this model is lower than for the base model. Maximum speed in the sample of vessels ranges between 6.2 and 7.1 knots, with a threshold fuel price above which towing speed decreases to between 0.49 and 0.67 Euro l^{-1} (Table 5). Including a third mechanism—catch efficiency having a sigmoid relationship with towing speed—further improves the fit, with log likelihood of 323.5. The AIC indicates that this is the preferred model (Table 5). The structure of model 3 fits the data better because it predicts a decline in towing speed with increasing oil price that is less steep. This is because catch efficiency declines at lower speeds, and benefits decrease non-linearly with decreasing towing speeds. The range of fuel prices at which the breakpoint occurs is 0.42–0.64 Euro l^{-1}, hence lower than in model 2. The largest reduction in towing speed as a result of the increase in fuel price is predicted for vessel no. 986, which reduces its towing speed by 14%. Fuel use reduction resulting from changes in fishing speed range between 0 and 177 l h^{-1}. This is a reduction of up to 40% with a population median of 9%.

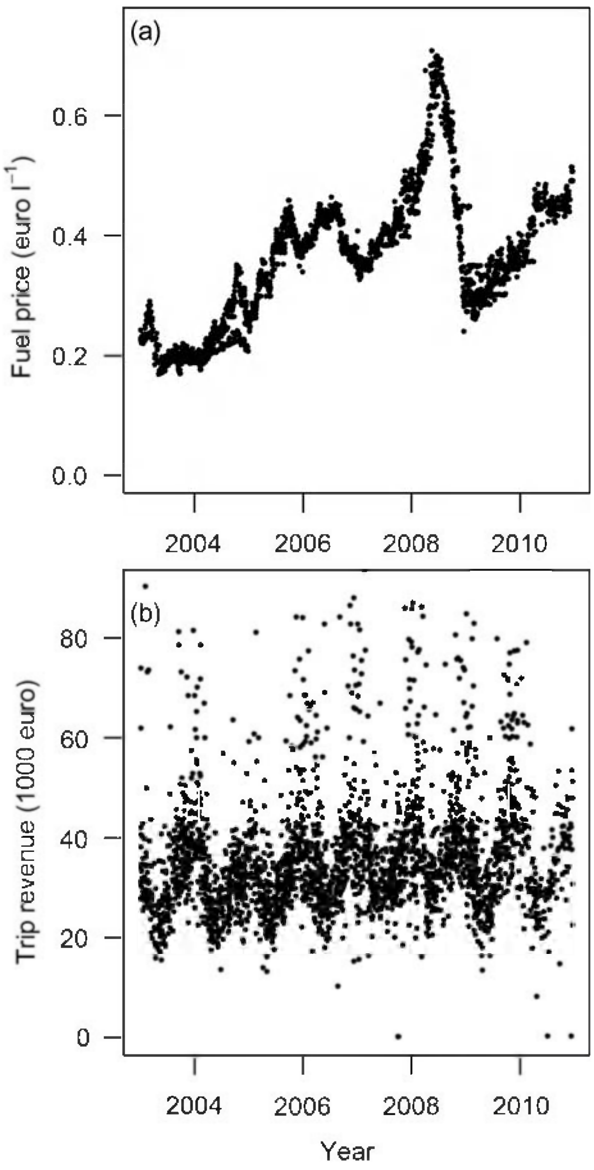

Figure 4. Time-series of (a) fuel price paid per trip and (b) revenue per trip for the vessels in the sample.

Distance to fishing ground

In order to test whether fishers respond to the increase in fuel price by fishing closer to port, the maximum distance recorded during a fishing trip was regressed against fuel price using quantile regression. The results show that the lower quantiles (<0.15) showed no response to the increase in fuel price, reflecting that fishers already fishing close to port were not affected. Those fishing at larger distances were increasingly affected by increasing fuel price and fished closer to port (Figure 7).

Discussion

Our simple model indicates that optimal towing speed is determined by fish density, fish price, and fuel cost. Optimal towing speed decreased with fuel cost and increased with revenue. The shape of the relationship depends on the catch efficiency–towing speed relationship. While towing speed is independent of distance to the fishing ground, the choice of fishing ground is affected by changes in fishing costs and revenues (Sampson, 1991; Poos *et al.*, 2010). If the cost of fishing increases or the revenue rate decreases, fishers are expected to fish closer to port. This prediction is supported by our data showing that beam

Table 3. Analysis of variance results for the effects of both fuel price and vessel on towing and navigating speed.

Source		Towning Speed				Navigating speed			
	d.f.	Sum of squares	Mean squares	*F*-value	*Pr* > *F*	Sum of squares	Mean squares	*F*-value	*Pr* > *F*
Vessel	12	174.0	14.50	351.5	<0.001	298.1	24.84	49.1	<0.001
Interaction	13	27.29	2.09	50.9	<0.001	165.0	12.70	25.1	<0.001
Residual	2 756	113.7	0.04			1 395.5	0.51		

Table 4. Estimates of the slope and standard error of towing and navigating speeds resulting from the linear regression model.

Vessel no.	Towing				Navigating			
	Slope estimate	s.e.	*t*-value	*p*-value	Slope estimate	s.e.	*t*-value	*p*-value
8	−0.328	0.13	−2.55	0.011	−2.73	0.45	−6.06	<0.001
10	−0.348	0.11	−3.26	0.001	−2.50	0.37	−6.68	<0.001
211	−0.004	0.12	−0.04	0.972	0.05	0.41	0.11	0.910
214	−1.203	0.11	−11.29	<0.001	−1.44	0.37	−3.86	<0.001
215	−0.673	0.16	−4.10	<0.001	−3.18	0.58	−5.52	<0.001
226	−0.062	0.11	−0.54	0.589	−2.08	0.40	−5.21	<0.001
326	−1.397	0.11	−12.95	<0.001	−0.78	0.38	−2.07	0.039
355	−1.106	0.14	−7.79	<0.001	−2.31	0.50	−4.64	<0.001
728	−0.179	0.33	−0.55	0.584	0.47	1.15	0.41	0.683
942	−1.078	0.20	−5.36	<0.001	−2.17	0.70	−3.08	0.002
986	−1.496	0.15	−10.27	<0.001	−2.90	0.51	−5.68	<0.001
1024	−1.324	0.15	−8.75	<0.001	−2.88	0.53	−5.43	<0.001
1248	−0.838	0.11	−7.77	<0.001	−3.27	0.38	−8.65	<0.001

The *t*- and *p*-values result from the test for the null hypothesis of a zero slope.

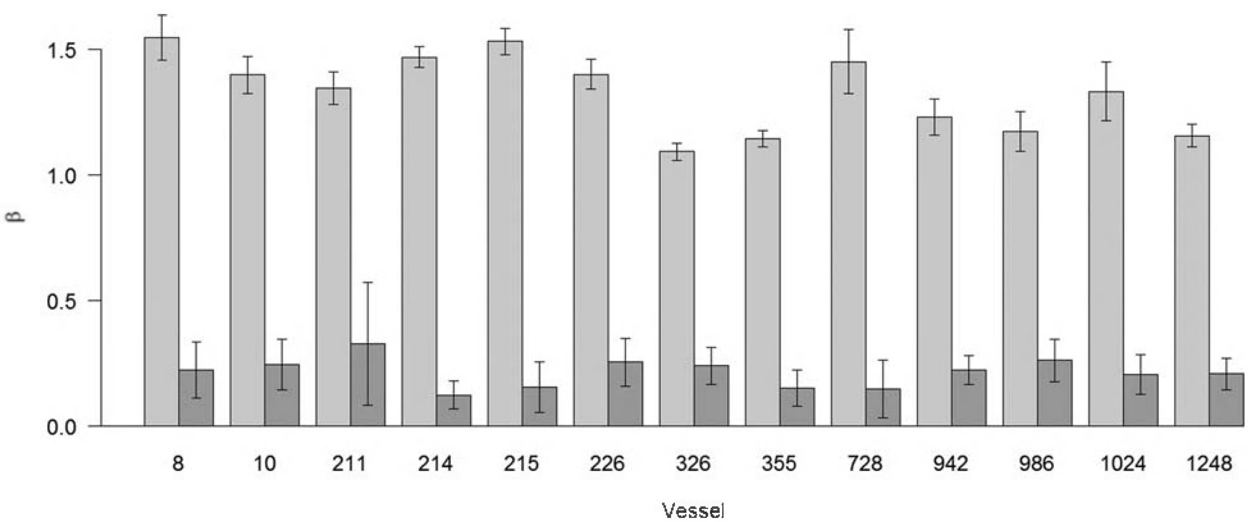

Figure 5. Fuel consumption parameter estimates for towing (β_t; light grey bars) and navigation (β_n; dark grey bars) for the vessels in the sample. Error bars indicate 2 s.e.

trawlers fish closer to home in response to fuel price increase. However, it should be noted that changes in fishing rights of the main commercial species (Quirijns *et al.*, 2008; Poos *et al.*, 2010) may have contributed to the observations that fishing occurred closer to port. Similar responses have been reported for the Danish fishing fleets (Bastardie *et al.*, 2010). Fuel-saving measures observed in this study are part of a larger number of changes in Dutch fisheries, such as increasing use of lighter "electric pulse beam trawl" gear (Polet *et al.*, 2005) and "sum wing beam trawl" gear. These gears are lighter and require less fuel (ICES, 2011b), also because these gears are towed at lower speeds ($\pm$ 5.5 knots).

Important for our results is that the steepness of the optimal fishing speed as a function of fuel price depends on the exponent in the relationship between fuel consumption and vessel speed. The lower this exponent, the steeper the relationship between optimal towing speed and fuel price. In our model, we followed Ronen (1982) and Corbett *et al.* (2009) in assuming that fuel consumption scales to the cube of vessel speed. In reality, the relationship between fuel consumption and vessel speed is likely to be more complicated and affected by wave action and wind acting on the vessel, design of the propulsion system, and drag of the gear in the water. For a beam trawler, resistance of the bottom components of the gear, particularly the tickler chains ploughing the sea bed, adds to gear drag. No empirical estimates of the effect of vessel speed on fuel consumption are available for beam trawlers, but Prat *et al.* (2008) modelled the contribution of different gear components to the drag of an otter trawl and assumed that drag of the gear scaled with the square of the speed. Future studies should measure fuel use of trawlers, as was done by Sala *et al.* (2011) for semi-pelagic pair trawlers in the Adriatic Sea. In addition, measurements on catch efficiency as a function of towing speed can improve parameter estimates used in the model. Currently, we must rely on comparisons between the commercial fleet and research vessel surveys; in effect, we are forced to assume the steepness of the relationship.

Our estimates of towing speed are higher than the estimates of Beare and Machiels (2012). The difference may be ascribed to a different method for classifying activity mode for VMS data or

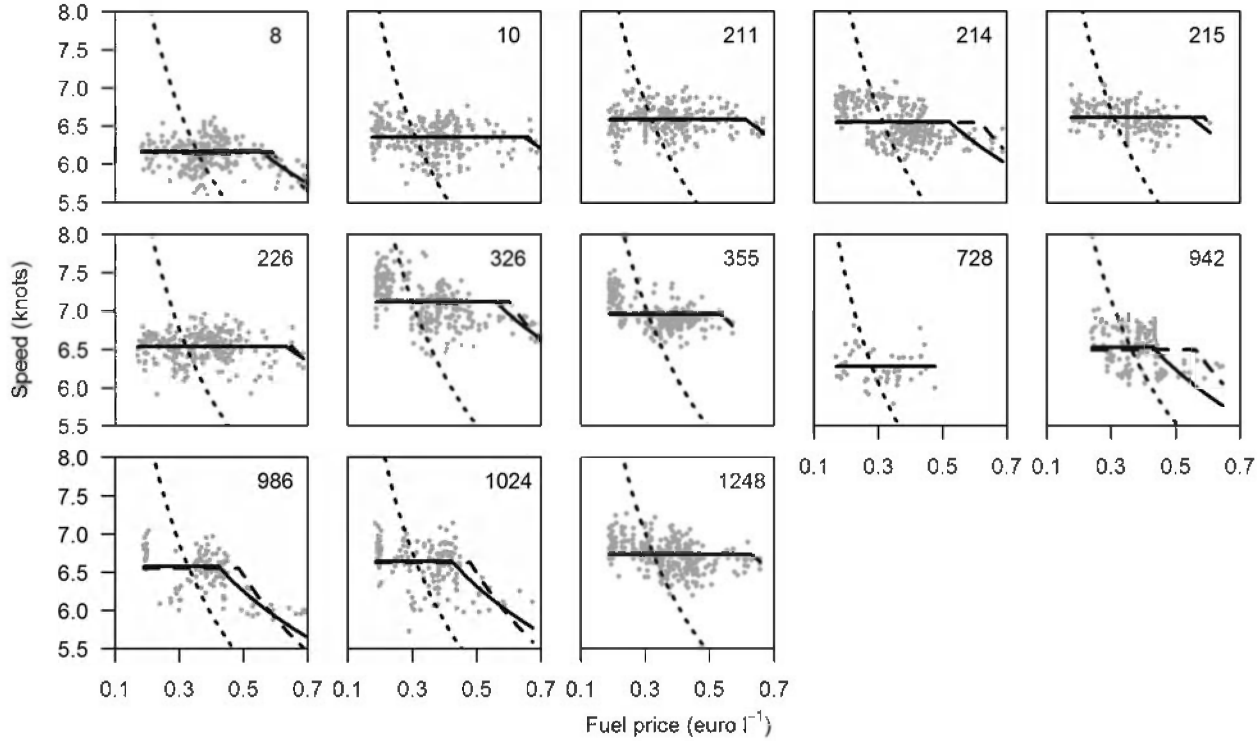

Figure 6. Relationship between observed towing speed and price of fuel per trip, and the three fitted optimality models of increasing complexity. Model 1 (dotted); model 2 (dashed) includes a maximum towing speed; and model 3 (drawn) includes a maximum towing speed and catch efficiency that decrease with towing speed.

Table 5. Model characteristics for the three models (see text).

Characteristic	Model		
	1	2	3
Log likelihood	−3875.6	280.2	**323.5**
Number of model parameters	14	27	**27**
AIC	7 779	−508	**−593**
Range in H (knots)	NA	6.2−7.1	**6.2−7.1**
Range in fuel price breakpoint (Euro l^{-1})		0.49−0.67	**0.42−0.64**

Model 3 (in bold) is the model that is preferred based on the Akaike information criterion.

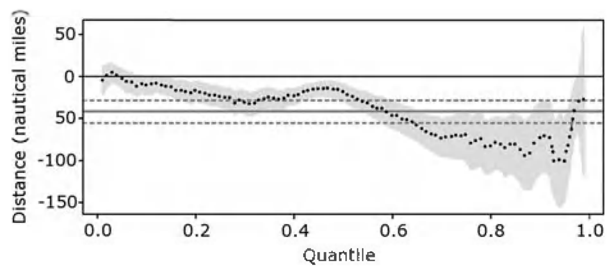

Figure 7. Slope of the quantile regression of maximum distance to the fishing ground relative to fuel price. The grey area indicates 95% confidence bands. Horizontal dark grey line indicates average slope, within 95% confidence bands (dashed).

the different selection of vessels. Whereas Beare and Machiels (2012) used a fixed speed range for all vessels and all years, we used a mixture analysis for each vessel and year separately to allow for intervessel differences in towing speed and changes in vessel speed during the study period. Further, Beare and Machiels (2012) used the average of the entire beam trawl fleet between 1400 and 1600 kW. In contrast, we used only vessels for which economic data were available and only data from trips using conventional tickler chain beam trawls rather than "electric pulse beam trawling" or "sum wing beam trawling" (Polet *et al.*, 2005; B. van Marlen, pers. comm.).

Our analysis provides support for the hypothesis that fishers respond to an increase in fuel price by reducing their towing speeds. The response varied across vessels, with three of the 13 vessels not showing a change in towing or navigation speed with the price of fuel. For one of those vessels, there was a limited number of observations, and the highest fuel price was below the price where other vessels maintained their maximum towing speed. For the other two vessels not showing a significant response, the range in fuel price was sufficiently wide to expect a significant response. We do not know where these individual differences in the response come from, but our results indicate that these two vessels did not have a particularly low fuel consumption parameter that could explain the lack of response. For the ten vessels that showed a response to the increase in fuel price, the threshold as well as the slope of the optimal towing speed with fuel price differed across vessels. Differences in response between vessels is not surprising. Although we selected a homogeneous sample with regard to engine power, vessels differed in other characteristics, such as age of the hull or engine, propulsion system, nozzle, etc., and other non-quantifiable aspects of costs and profits that may affect their optimal response (Marchal *et al.*, 2006; Rijnsdorp *et al.*, 2006; Eigaard, 2009).

Only after a maximum vessel speed and a relationship between catch efficiency and fishing speed were included in the model was a reasonable fit obtained. In trawl fisheries, towing speed is an important parameter affecting catch efficiency (Winger *et al.*, 2000). In the beam trawl fishery, the increase in towing speed was one of the key characteristics that resulted in the "arms race" in the flatfish fishery in the 1970s and 1980s (Rijnsdorp *et al.*, 2008). The effect of towing speed on catch efficiency may be related to interference or exploitation competition among vessels. Interference competition may occur due to the response of fish to the fishing gear. On a heavily fished ground, fish may be more alert and reduce their response time in avoiding approaching gear. This mechanism implies that the effect of towing speed on catch efficiency is dependent on the number of vessels on the same fishing ground (Rijnsdorp *et al.*, 2000; Poos and Rijnsdorp, 2007). Exploitation competition (Polis *et al.*, 1989) may affect catch efficiency when fishers towing at higher speed catch a larger portion of the fish aggregated on a local ground.

Even with the introduction of a maximum vessel speed and a relationship between catch efficiency and fishing speed to the model, the fit of the model was not optimal, and could be improved if a shallower relationship between towing speed and fuel costs could be predicted by our model. Such a functional response is only possible if the exponent in the relationship between fuel consumption and vessel speed is >3, or if the effect of vessel speed on catch efficiency is larger than we assume through competition or other processes described above. Alternatively, one might challenge the assumption of fishers as perfect profit maximizers. Although this assumption dominates the fishery literature, it is known that fishers do not necessarily behave as such. Van Ginkel (2007) describes how beam trawl fishers aim to maximize total catch volume more than net profits. If our fishers would have been catch maximizers, one would not expect to have observed a decrease in towing speed with increasing fuel price. The observation that two out of 13 fishers did not show a response to a substantial change in fuel price may indicate that these fishers might have been catch maximizers. The other fishers might have fallen somewhere between profit and catch maximizers. This hypothesis may well explain why the observed decrease in towing speed is not as strong as model expectations.

Change in towing and navigation speeds in response to fuel price implies that effective fishing effort has been reduced, because the swept-area per unit towing time has been reduced. Also, because navigating speed has been reduced, more time is spent navigating to and from fishing grounds. However, our results also indicate that fishing takes place closer to port, thus reducing time spent navigating to and from fishing grounds. Given that recorded fishing effort is often in days absent from port, these changes in fishing effort may go unnoticed. Failure to correct for change in speed implies that catch per unit of effort, as an indicator of stock biomass, will underestimate biomass (Beare and Machiels, 2012).

Conclusions

Beare and Machiels (2012) recently showed a population-level decrease in fishing speed in response to increasing fuel prices. Here, we studied 13 individual vessels in the same period for which data on fuel use and prices are available. Analyses indicate that the population-level decrease in average towing speed can be attributed to a response of vessels that reduce towing speed. In addition, vessels have reduced navigating speed in response to increasing fuel prices, and fish closer to port. A simple model including effects of towing speed on catch efficiency and a maximum speed determined by engine power explains the observations for the sample vessels. However, the predicted response in the model is stronger than what is observed for the vessels. The reason for this discrepancy is unknown, but could be (i) the result of unincorporated processes shaping the relationship between towing speed and fuel price; or (ii) the result of fishers not being perfect profit optimizers.

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