CEEPA Discussion Paper No. 40
CEEPA Discussion Paper Series ISBN 1-920160-01-09
Discussion Paper ISBN 1-920160-41-8, October 2008

DETERMINANTS OF NON-COMPLIANCE WITH LIGHT ATTRACTION REGULATION AMONG INSHORE FISHERS IN GHANA

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[♣] This research work was carried out with the aid of a grant from the Centre of Environmental Economics and Policy in Africa (CEEPA) (www.ceepa.co.za), financed by the Swedish Development Cooperation Agency (SIDA). I am very thankful to David Starrett, Thomas Sterner, Rob Dellink, Marty Luckert, Edwin Muchapondwa, and all the participants at the CEEPA research workshop in 2007 in Pretoria for their invaluable comments.

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Correct citation: Akpalu, W 2008. Determinants of non-compliance with light attraction regulation among inshore fishers in Ghana. CEEPA Discussion Paper No 40, Centre for Environmental Economics and Policy in Africa, University of Pretoria.

Core funding for CEEPA comes from the University of Pretoria. CEEPA receives supplementary funding from various donors including the Swedish International Development Cooperation Agency (SIDA), GEF, NRF South Africa, NOAA (USA), IDRC.

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Department of Agricultural Economics, Faculty of Natural and Agricultural Sciences
University of Pretoria; PRETORIA 0002, Republic of South Africa

ISBN 1-920160-40-X
First published 2008
Series ISBN 1-920160-01-9

Printed and bound in South Africa by University of Pretoria

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EXECUTIVE SUMMARY

In many developing coastal countries, wild fish stocks have been overexploited. Moreover, fishing techniques have evolved which have exacerbated the problem of stock depletion. In Ghana, some inshore fishers acquire and illegally use light attraction equipment to improve their efficiency. This equipment includes a fire torch, pressure kerosene lamp, gas light lamp, and battery or generator assisted incandescent lamp. Since this crime is committed repeatedly until detection, this study extends the fishery crime model of Akpalu (2008) to investigate the determinants of the non-compliance with the regulation.

Two empirical models have been estimated: a Logit model to investigate the factors determining violation of the regulation and Maximum Entropy Leuven Estimator (MELE) (i.e. a semi-parametric model), due to limited data on violators, to estimate the severity of violation of the regulation. We found that increased risk of punishment (i.e. probability of detection) and severity of punishment (i.e. penalty) decrease the violation rate and older skippers are less likely to violate the regulation. The impact of the probability of detection is stronger than that of the penalty and the age of the skipper has the strongest impact on the violation rate. Individual discount rates, number of dependents, perceived social pressure and unfairness of the regulation positively affect the violation rate. For those fishers who violate the regulation, the investment in the light attraction equipment, which is a proxy for severity of violation, negatively affects the probability of detection and penalty. On the other hand, the severity of violation positively affects individual discount rate, fishing effort, social pressure and the age of the skipper, and the extent to which the fisher believes the regulation will protect the stock.

The policy implications are as follows. First, fishers could be discouraged from violating the regulation or those who violate will decrease the severity of violation if the enforcement effort and/or the penalty increases. Second, since we found discount rates to be generally high, which could be an indication that the fishers are credit constrained due to imperfections in the credit market, any policy that addresses such imperfections in the credit market is likely to reduce the violation of the regulation. Third, since younger fishers are more likely to violate the regulation than the older ones but among those who violate the regulation, the older ones have higher severity of violation of the regulation than the younger ones, the fishery department should direct more resource to targeting the middle-aged fishers. Finally, the fishery department should direct surveillance to bigger boats since bigger boats have higher investment in light attraction equipment.

1. Introduction

From the late 19th century and early 20th century, Ghana's population increased considerably triggering the demand for fish. The fishery sector responded to the increased demand by undergoing some considerable changes. These include the introduction of improved fishing gears such as the purse seine net and synthetic netting materials, outboard motors, and improvement in fish processing and storage facilities (Koranteng, 1992). Presently, artisanal and semi-industrial fishing are the most important direct and indirect employment generating activity in the entire coastal zone of the country. It has been estimated, for example, that the artisanal fishery sub-sector supports about 1.5 million people (FAO, 1998) and of the total marine annual fish catch, between 70% and 80% come from the artisanal fisheries (FAO, 1998), with the rest coming from the semi-industrial and industrial fishing vessels. Since the resource is essentially managed as an open access with some gear restriction, the over-capitalization of the artisanal and semi-industrial fishery has eventually resulted in over harvesting of the nation's inshore wild fish stock. For example, after a sharp increase in artisanal catch per boat from 27.4 to 35.3 between 1989 and 1992, it declined from 1992 through 1995 although fishing techniques improved and the number of crew per boat also increased. The most recent data available show that the lowest figure for the catch per boat was recorded in 2001 (Mills et al., 2004 cited in Akpalu, 2008).

In spite of the declining average size and quantity of catch due to the overcapitalization, fishing techniques have evolved to the use of destructive fishing gears, which is further exacerbating the problem of over harvesting. The light attraction, which is mainly used by purse seine gear (i.e. inshore/semi-industrial vessels), is the technique that involves the use of artificial light in the night when the moon is out to attract and aggregate fish so that with any given effort, more fish could be harvested. Examples of the source of light include a fire torch, pressure kerosene lamp, gas light lamp, and battery or generator assisted incandescent lamp (Bannerman and Quartey, 2004). According to Bannerman and Quartey (2004), catch of small pelagic fishes increased from 450 metric tons in 1999-2000 to 7000 metric tons in 2001-2003 when the use of light attraction equipment intensified. With fishing efforts exceeding sustainable levels in the sector coupled with the use of destructive fishing gears such as the light aggregation, it is likely that the inshore fishery may eventually collapse. This poses a serious threat to food security and sustainable livelihoods which goes beyond the fishing communities. To reverse or halt the over fishing, it is imperative to investigate the reasons for non-compliance with the regulations and then formulate policies accordingly.

In the fisheries economics literature, the theoretical model of crime developed by Becker (1968), Ehrlich (1973) and Block and Heineke (1975) have been used to empirically investigate determinants of fishery crimes. However, as noted by Akpalu (2008) this model which has been applied to closed areas, quantity restriction, or gear restrictions has considered a situation where the potential violator faces a one-period decision problem of maximizing an expected utility[1]. For crimes that are committed repeatedly, such as the acquisition and use of light attraction or illegal nets, the potential offender considers the stream of benefits obtainable from the crime and therefore has to be modelled as dynamic model, which involves discounting. In this paper a dynamic deterrence model of crime is presented following Akpalu (2008) and tested with data from inshore fishers in Ghana. It is noteworthy that although the theoretical framework for this paper draws on Akpalu's work, this paper extends the model to address a different regulation with potentially different violators (i.e. different sample is considered). Factors such as individual discount rate, perceived probability of detection, expected fine, age of the fisher, social pressure, fairness of the regulation, among other possible factors have been investigated. The findings, which are interesting and conforms to the theoretical predictions show that perceived instantaneous conditional probability of detection and expected fine are negatively related to the decision to violate and the severity of violation (of which the replacement cost of the light attraction equipment is used as a proxy)[2]. Secondly, the individual discount rate and perceived social pressure are positively related to both the decision to violate and the severity of violation. Thirdly, while younger fishers are more likely to violate the regulation, the older cohorts among the younger fishers have higher severity of violation implying that the fisheries department must target younger adults. Furthermore the fishers who strongly agree that the light attraction regulation is unfair or

[1] Examples of the static crime model applied to fisheries are Sutinen and Andersen, 1985; Anderson and Lee, 1986; Sutinen and Hannessey, 1986; Furlong, 1991; Kuperan and Sutinen, 1994; Charles et al., 1999; Sutinen and Kuperan, 1999; Hatcher et al., 2000; Hatcher, 2005; and Chavez and Salgado, 2005.

[2] Although the severity of use may also depend on the frequency of use, the fishers were reluctant to provide that additional information during the pilot visit so this information was not obtained in the survey. Moreover, since the fishers do not keep proper records there was also a problem of accuracy in recalling this information.

have relatively more dependents are more likely to violate the regulation. On the other hand, for the fishers who violate the regulation, the severity of violation increases with the strength of the conviction that the regulation is intended to protect the stock.

The rest of the paper is organized as follows. The theoretical model is presented in section 2 followed by some empirical models in section 3. Section 4 has the data description and discusses the results and section 5 presents the conclusions of the paper.

2. The Theoretical model

The theoretical framework for this research is a dynamic model of fishery crime, which follows Akpalu (2008). Consider a standard Schaefer model in which the level of harvest perfectly correlates with the level of effort for any given level of stock. Further, assume that the catchability coefficient is a function of the use of light attraction so that with any given level of stock and effort, the more fish is caught the more the severity of use of the light equipment. Suppose that a potential violator i of the light attraction regulation has a profit function given by $\pi^i(\alpha(l)_{it}, E_{it}, x_t, k, p_x)$, where ($x_t$) is a given stock within the management area; $\alpha(l)_{it}$ is the catchability coefficient which is a function of the severity of use of the light attraction equipment (i.e. l); E_{it} is an index of fishing effort; k is a common fixed cost of harvest which is independent of the level of use of the light attraction; and p_x is price per kilogram of harvest which is assumed to be constant over time. If the fisher does not use the light attraction, then the catchability coefficient is normalised to 1, and it is greater than 1 if the fisher uses it.

The fishery under consideration is organized as an open access with some gear restrictions and is characterized by unpredictable seasonal upwelling that produces plankton, on which the fish feed (Akpalu, 2008). It is therefore impossible for fishers to predict the trend of the fish stocks. We suppose for simplicity, but without losing generality, that a fisher's best forecast of future stock is the present stock and therefore takes the stock as given. It is also noteworthy that in an open access fishery, the stock has no capitalized value to an individual fisher. The general specification of the profit function for the fisher, if he violates the regulation, is

$$\pi^i(\alpha(l)_i, E_i, k, p_x, c) = p_x \alpha(l)_i E_i x - cE_i - k \,, \tag{1}$$

where cE_i is individual specific cost function for the harvest (the time subscripts have been suppressed for notational convenience), c is constant per unit cost of effort, $\frac{\partial \alpha(l)}{\partial l} > 0$ and $\alpha(0) = 1$. On the other hand, if the fisher does not use the light attraction equipment, his profit is $\pi^i(1, E_i, k, p_x, c) = p_x E_i x - cE_i - k$. Assume that the fisherman is not a pure profit-maximizing agent but derives disutility (say feels guilty) directly from using the illegal equipment and the disutility is scaled by a vector of the fisherman's socio economic characteristics and perception variables (Φ) so that $z^i(l, \Phi)$ defines the function (Akpalu, 2008). The utility function may then be re-stated as

$$u^i(\tilde{\alpha}(l)_i, E_i, x, \Phi_i, k, p_x, c) = \pi^i(\alpha(l), E_i, x, k, p_x, c) + z^i(l; \Phi) \,, \tag{2}$$

where $z_l^i < 0$ and $\tilde{\alpha}(.)$ incorporates the disutility from fishing illegally. By implication, if the fisherman does not violate the regulation then $u^i(1, E_i, x, \Phi_i, k, p_x, w)$, with $z^i(0) = 0$ by some normalization.

If a fisher is caught using the illegal equipment he receives a fine defined by the expression $F^i(l_i) = \overline{f}_i + \tilde{f}_i(l_i)$, where $\overline{f}_i$, the perceived fine, is the product of a fixed fine and each fisherman's perceived probability of being fined given that the illegal fishing activity is detected (q_i) (i.e. $\overline{f}_i = q_i \overline{f}^i$); and $\tilde{f}_i(l)$ (with $\tilde{f}_l > 0$) is the expected penalty, which depends on the severity of violation (i.e. seizure of the light attraction equipment). As in Akpalu (2008) and Davis (1988), suppose that each violator does not know the exact time the detection will occur but only some probability distribution of the time of detection denoted by $g_i(l_i, t)$, where the probability that detection would have occurred at time t in the future is the cumulative density function (cdf), $G_i(t)$. The expected present value of the penalty can then be stated as $\int_0^\infty F_i(l_i) g_i(l_i, t) e^{-\delta_i t} dt$ and the resultant illegal-legal two-segment dynamic problem is

$$V^i(\tilde{\alpha}(l), E_i, x, k, p_x, c) = \int_0^\infty e^{-\delta_i t} \begin{Bmatrix} u^i(\alpha(l), E_i, x, \Phi_i, k, p_x, c)\left(1 - G_i(t)\right) + \\ u^i(1, E_i, x, \Phi_i, k, p_x, c)G_i(t) - F_i(l_i)g_i(l_i, t) \end{Bmatrix} dt\,, \qquad (3)$$

where $V^i(.)$ is the value-function and δ_i is the individual benefit discount rate which is assumed to be positive. The illegal fisher will maximize profit from the illegal catch until it is detected but after the detection he will have to maximize profit from only legal harvesting[3]. Furthermore define the probability that the illegal activity will be detected within a very small interval of time t given that it had not been detected in the past as $p^i\left(l_i\right)$ so that $p^i\left(l_i\right) = \dfrac{g_i(l,t)}{(1-G_i(t))}$. Let $p^i\left(l_i\right) = \bar{p}_i + \tilde{p}(l_i)$ where $\bar{p}_i$ is exogenous and could be influenced by increased enforcement effort. Moreover if l_i is assumed to be time invariant and the fisher commits to some optimum level of effort over time, then $(1-G_i(t)) = e^{-p^i(l)t}$ and $g_i(l,t) = p^i(l)e^{-p(l)t}$. Equation (4) is obtained if the expression for the probability distribution (i.e. $g(l_i,t)$) is substituted into the objective function and all other values are supposed to be constant over time.

$$V^i = \frac{u^i(\tilde{\alpha}(l)_i, E_i, x, \Phi_i, k, p_x, c) - u^i(1, E_i, x, \Phi_i, k, p_x, c) - p^i\left(l_i\right)F^i(l_i)}{\delta_i + p^i\left(l_i\right)} + \frac{u^i(1, E_i, x, \Phi_i, k, p_x, c)}{\delta_i} \qquad (4)$$

Equations (4) could be maximized with respect to l_i (the variable of interest) and E_i. Note that the first and second terms on the right hand side of the equation are the expected returns from fishing illegally and fishing legally, respectively. If the first term is positive then it is worthwhile to invest in the illegal equipment (Chang and Ehrlich, 1985; Akpalu, 2008). Also, as noted by Akpalu (2008), the importance of the discount rate in violation stems from the fact that if l_i affects $p^i(l_i)$ then l_i affects future profits and the current value of this effect depends on δ_i. The following signs are easily obtainable from the Hessian matrix derived from equation (4) (see Akpalu, 2008 for similar derivations):

[3] It is supposed that offenders do not repeat the crime after they are caught because as noted by Akpalu (2008) the inshore fishermen are known to live in abject poverty and may not be able to reinvest in the equipment if it is seized.

$\frac{\partial l_i^*}{\partial \bar{p}_i} < 0$, $\frac{\partial l_i^*}{\partial \bar{f}_i} < 0$ and $\frac{\partial l_i^*}{\partial \delta_i} > 0$. Furthermore, in reality the optimal effort (i.e. E_i^*) precedes the investment in light attraction equipment, hence l_i^* depends on E_i^*. Note that the specific functional forms of the utility function has not been specified. Therefore, we can only characterize the relationship between the supply of violation and its possible determinants. Since p_x, w, k and c are not individual specific but apply to all fishermen, these parameters will be captured by the intercept of the regression. Second, from the specification of the catch function, the severity of violation will be a function of the level of stock and since the stock level does not vary across the fishers, it is not an argument in the empirical model. Finally, the socio-economic variables in the vector Φ_i includes the fisher's age (A_i), wealth (W_i), whether the fisher belongs to a credit association or not (CR_i), the number of dependents the fisher has (DP_i). The perception variables are the fisher's perceived social pressure (SP_i) and fairness of the regulation (FR_i) (see Kuperan and Sutinen, 1994; Sutinen and Kuperan, 1999; Hatcher et al., 2000; Akpalu, 2008). From equation (4), the general form of the supply of violation function is specified as

$$l_i^* = l_i^* \left(\bar{p}_i, E_i, \delta_i, \bar{f}_i, \Phi(A_i, W_i, DP_i, CR_i; SP_i, FR_i) \right), \tag{5}$$

It is hypothesized that, for example, increasing social pressure, measured by the perception of the proportion of fishermen who violate the regulation would motivate a fisherman to increase the severity of violation. Similarly, a fisherman who is more inclined to perceive the regulation to be unfair is likely to have higher severity of violation, all other things being equal. In addition, the inclusion of age in the model is motivated by findings in the age-crime profiling literature that younger adults are more likely to commit a crime than older ones (see e.g. Leung, 1994; Akpalu, 2008).

3. The Empirical model

Two empirical models are estimated. The first is a simple logit regression for estimating the determinants of the decision to violate. Secondly, due to the limited data on violators of the regulation (49 observations), both the Ordinary Least Square (OLS) estimation techniques and Maximum Entropy Leuven Estimator (MELE), which is a semi-parametric estimation technique, are used to estimate the equation for the severity of violation (see Paris, 2001 for elaborate discussion on MELE). All other things being equal, the more investment a fisher makes in the light attraction equipment the more advantage he/she has over the fish stock hence the more severe is his/her violation. Therefore, investment in light attraction regulation is used loosely as a proxy for the severity of violation of the regulation. It must be noted that equations that are empirically estimated are generally assumed to be linear. The coefficients are not directly derived from the general specification of the supply of violation equation (i.e. equation 5) and only the expected signs guide the empirical model. We present the procedures for the Logit regression and MELE below.

The logit model

Since the dependent variable is binary (i.e. violate the regulation or not) the logit regression is specified as follows:

$$\ln\left(q_i/(1-q_i)\right) = F(\bar{p}_i, E_i^*, \delta_i, \bar{f}_i, \Phi(\bullet); \beta_i, \varepsilon_i)\,, \tag{6}$$

where ε_i is the error term with a logistic distribution, q_i is the probability that a fisher i violates the regulation and β_i is the vector of coefficient of all the explanatory variables. Since the perceived probability of detection is likely to be endogenous, it is regressed on E_i and its predicted value is used as an instrument. Furthermore, since the perceived probability of detection is likely to be endogenous, it is regressed on ownership of the fishing vessel, size of the boat and crew size, and its estimated value is used as an instrument in the logit regression. In addition, following Akpalu (2008), the perceived proportion of fishermen who violate the regulation will be used as an indicator for social pressure. In section 4, we discuss how the data was collected on all the variables of interest including the probabilities and the rate of time preference.

Maximum Entropy Leuven Estimator (MELE)

The MELE is a semi-parametric estimator that was developed by Paris (2001). The method is an extension of the Generalized Maximum Entropy (GME) method (see e.g. Golan et al., 1996; Paris and Howitt, 1998; Lence and Miler, 1998). The Maximum Entropy Estimators belong to a class of estimators that are customarily used in engineering and physics. These estimators have been shown to yield low mean square error in small samples and to be particularly good at dealing with small samples and/or multicollinear regressors in behavioral models. Like the GME the technique involves maximizing an entropy function to obtain parameter values of a behavioral model. However, unlike GME the MELE does not impose support values on the parameters to be estimated. Since estimated parameters are generally very sensitive to the choice of support values, the MELE is superior to the GME (Paris, 2001). Like the other Entropy estimators, the MELE was motivated by the theory of light in physics. According to the theory the probability that a photomultiplier is hit by a photon reflected from a sheet of glass is equal to the square of its amplitude. As a result, if the parameter to be estimated in the severity of violation equation and for that matter any behavioral model has amplitude or is normalized in a dimensionless manner, then the square of the amplitude will define the probability. To illustrate this consider a linear regression model of the form

$$y_i = z\beta_k + u_i \tag{7}$$

where y_i is dependent variable (e.g. the replacement cost of the light attraction equipment l_i^*), z is the vector of all the explanatory variables (e.g. $F(E_i, \bar{p}_i, \delta_i, \bar{f}_i, \Phi(\bullet))$, β_k is the associated vector of coefficients and ε is the error term.

Suppose that a linear relationship exists between the severity of violation and the explanatory variables in equation (7) and let the sum of the coefficients in the equation be

$$L_\beta = \sum_k \beta_k^2 \tag{8}$$

A unit-free or amplitude of each k is obtained if each parameter is divided by the square root of equation (8) (i.e. $\beta_k / L_\beta = \beta_k \Big/ \sqrt{\left(\sum_k \beta_k^2\right)}$). Paris (2001) then defines the probability for each k as

$$p_{\beta_k} = \beta_k^2 / L_\beta \tag{9}$$

Using equations (7), (8) and (9) as constraints, equation (10) is maximized with respect to the three unknowns (i.e. β_k, p_{β_k} and u_i). Thus

$$\max H(p_{\beta_k}, L_\beta, u_i) = -\sum_i p_{\beta_i} \ln(p_{\beta_i}) - L_\beta \log(L_\beta) - \sum_i u_i^2 \tag{10}$$

s.t.

Equations (7), (8) and (9),

with $p_{\beta_k} \geq 0$ and equation (7) is assumed to be a linear function. As noted by Paris (2001) the term $L_\beta \log(L_\beta)$ prevents L_β from taking very large values. The General Algebraic Modeling System (GAMS) was used for this non-linear optimization program. The description of the data and the results are presented in the next sections.

4. Survey design and data description

The data for the analyses was collected through a survey of fishermen in Elmina in the Central Region, Axim and Secondi in the Western Region, and Tema in the greater Accra Region of Ghana. A random sample of 118 skippers was interviewed. A questionnaire was administered to each of the skippers in a face-to-face interview. Out of this number, only 3 refused to take part in the survey giving a participation rate of 97%. To guarantee anonymity and also gain the confidence of the fishers, an approval was sought from the chief fisherman who is highly respected by all the fishermen in each of the districts, before the questionnaires were administered to the skippers. Each beach was visited once to interact with the fishermen and to establish some trust before the questionnaires were administered during the second visit. Moreover the respondents were assured that the data was not going to be used against them and also that their responses would be treated with strict confidentiality. Although we also spoke to some officers of the district fishery departments to appreciate the problem, we did not directly involve them in the surveys.

The questionnaire included questions about demographic characteristics (e.g. age of skipper, marital status, number of dependents, wealth, membership of credit association (i.e. *susu* group), fishing experience); the types of fishing nets used, length of the fishing boat, whether the fisher uses any light attraction equipment or not, the replacement value of the light attraction equipment, the size of the fishing crew, the subjective instantaneous conditional probability of detection, the expected fine if caught, and a choice based experiment similar to that of Akpalu (2008) to compute the individual rate of time preference of each skipper. The descriptive statistics of the data is presented in Table 1 in the appendix.

To determine the individual discount rate, each respondent was asked to choose one of two hypothetical fishery projects. Project A could increase the skipper's income once by US100 at the end of the month in which the data was collected, and Project B could increase it once by US200 in three months' time[4]. After the choice was made, the respondent was asked to indicate the value for Project B that would make him indifferent between the two projects. The instantaneous individual discount rate is then computed as $\delta = \log(\alpha_2/\alpha_1)$, where α_2 is the amount quoted by the skipper, and α_1 is the amount Project A offers (US100). The extrapolated mean annual discount rate was 118%. Such high lending and discount rates have been found in Ghana (see Aryeetey,1994 who found informal quarterly lending rate of about 25-30%; and Akpalu, 2008 who found an average individual discount rate of 131%). As noted by Akpalu (2008) the high rate may result from the high rate of default and a high and volatile rate of inflation in Ghana of about 11-27%.

A five-point Likert-scale ranging from *strongly agree* to *strongly disagree* was used to measure the extent to which the skipper perceived the fishing regulation to be unfair and to protect the stock. As high as 36% strongly agreed that the regulation is unfair and only 10% completely disagreed. Also regarding the question of whether the regulation is to

[4] These figures are quite high compared to the average daily catch of US82 that was reported by the skippers.

protect the stock, only 9% of the respondents completely agreed compared to 51% who completely disagreed. This observation nevertheless lends credence to the high rate of violation of the regulation. The skipper's perception of violation rate was measured on a continuous scale and about 70% indicated that at least 50% of the fishers violate the regulation.

Out of the 115 respondents as high as 50 (43%) indicated that they use the light attraction equipment and the rest indicated that they do not have it. The average replacement cost of the equipment is US1001 with a very high standard deviation. We followed Akpalu (2008) and Hatcher et al. (2000) to communicate in a simple way the question on the perception of instantaneous conditional probability of detection to the respondents. The time frame for the conditional probability of detection is one year and the five-point scale ranges from *very high* (50% or more) to *very low* (1% or less).[5] The mean probability of the violators of the regulation is 16% which is about half of non-violators (31%). Also the perceived probability of being fined given detection is much higher for non-violators (17%) than violators (10%) of the regulation. These findings (i.e. the negative relationships) are consistent with earlier empirical works on supply of violations and consistent with expectations from our theoretical model (see e.g. Hatcher and Gordon, 2005; Akpalu, 2008). These variables were used in the empirical estimations.

5. Empiral estimations of violation functions

As indicated in the section on methodology, two equations have been estimated: a logit model for the determinants of decision to violate and MELE which is a semi-parametric estimation. The results from the two procedures are presented and discussed below.

The logit Estimation

The dependent variable of the logit model takes the value of 1 if the skipper violates the regulation and 0 otherwise. The estimation results are presented in Table 2 in the appendix. The pseudo R-squared of 0.45 indicates that the regression line is a good fit. As argued in the literature, the probability of detection is likely to be endogenous. As a result, the two-

[5] The five-point scale of the probability is as follows: very high (0.5 or more), high (around 0.25), quite possible (around 0.10), moderately low (around 0.05), and very low (0.01 or less).

stage-least-square estimation procedure was employed. Thus, the probability of detection was regressed on indicators of effort: the boat size, crew size and ownership of the fishing gear, and the predicted values were used in the logit regression. The results presented in Table 2 show that increased risk of punishment (i.e. probability of detection) and severity of punishment (i.e. expected fine) will discourage violation of the light aggregation regulation. Note that the expected fine is significant only at 15% level of significance probably as a result of the weak enforcement of the regulation.

Moreover, the effect on the increased risk of punishment on decision to violate is stronger. Indeed a 10% increase in the probability of detection will discourage about 13% of the violators while the corresponding increase in the penalty will decrease violation by only approximately 2%. As the face value it appears that policy makers could discourage violation by increasing surveillance rather than setting higher fines. However, since setting higher fines are generally costless while increasing enforcement effort is costly, this policy prescription is appropriate if the net benefit from increased enforcement exceeds that of the increased fine. Moreover, in order to establish the link between surveillance and perceived probability of detection, the perceived probability of detection was regressed on the number of times a fisher saw enforcement officers at the beach within the last year of fishing. In spite of the fact that recall could be poor among fishers who do not keep proper records, the simple regression results indicated a positive and significant relationship. Indeed on the average a fisher who sees an officer everyday would have a probability of 0.284 higher than the fisher who saw an officer once within the year.

Secondly as found in Akpalu (2008) the individual discount rate is positively related to the violation decision and a 10% increase in the discount rate will increase the violation rate by approximately 5% (albeit significant only at 10% level of significance). There are empirical evidence of positive relationship between levels of poverty and individual discount rate (e.g. see Lawrance, 1991; Holden et al., 1998). As a result, any policy that addresses the underlying causes of high discount rate, such as poverty eradication programs, are likely to lead to decreased violation and sustainable management of the fish stock. On the other hand with regards to the relative values of the discount rates, any policy that bridges the gap across the fishers is likely to reduce the severity of violation.

Furthermore, the age of the skipper is negatively related to and has the highest impact on violation with the coefficient being the most highly significant among all the explanatory variables (i.e. at 1% level of significance). It is therefore important that the fishery management policy and programs target relatively younger fishers.

Results from the Maximum Entropy Leuven Estimator

Due to the limited number of violators of the regulation and the possibility of high multicollinearity among some explanatory variables in the severity of violation equation, parametric estimation methods are likely to yield inconsistent estimates. Note that as indicated earlier, the replacement cost is used as a proxy for the severity of violation of the light attraction equipment. The results of the MELE are presented in Table 3 in the appedix. The choice of variables for the estimation is guided by the results from a parametric estimation (i.e. Ordinary Least Square (OLS) Estimation with robust standard errors). The results from the OLS have also been reported in the Table 3 for the purpose of comparison.

Except for the coefficient of the age of the skipper and the variable that indicate that the regulation is to protect the stock, all the other coefficients are similar in the two estimations. In addition, the probability of detection is significant but expected fine is not in the MELE, while the reverse is true in the OLS estimated results. Results from the two procedures however show a negative relation between the severity of violation and perceived probability of detection and expected fine. This implies that all other things being equal, fishers who on the average had higher severity of violation are likely to have a lower perception of the probability of detection. Furthermore, from the MELE, a 10% increase in individual discount rate will lead to over 12% increase in the severity of violation of the regulation. Moreover, the relationship between the proxy for fishing effort (i.e. boat) and the severity of violation is positive implying that enforcement effort should be directed to bigger boats.

Contrary to the results from the logit regression, with regards to the skippers who violate the regulation, the older fishers have higher severity of violation. The descriptive statistics show that the average and maximum age of the violators is 37 and 66 years respectively which are lower than the corresponding values for non-violators. Consequently, although younger fishers are likely to violate the regulation the older cohorts among these younger ones have higher severity of violation. Also, the skippers who indicated that the regulation could protect the fish stock, on the average, had higher severity of violation. The implication is that fishers who are aware that the fish stock is declining but could be protected by the regulation are quickly depleting the stock. As a result, providing information about the importance of the regulation to protect the stock without enforcing the regulation could be counterproductive. Since MELE is a semi-parametric estimation method, pseudo statistics were obtained from bootstrapping the estimated coefficients. To do this, a 150 random data set each with the same number of observations and variables as the original data was drawn. For each data set, the MELE was used to obtain the set of coefficients from which the standard deviations were computed. Moreover, the plot of the actual and fitted values of the severity of violation is presented in Figure 1 in the appendix. These plots provide some visual indication of the goodness of fit of the estimation.

6. Conclusions

In this study, we investigate the determinants of the decision to violate the light attraction regulation and the severity of violation. The theoretical model, which is based on Akpalu (2008) shows that individual discount rate and fishing effort among other factors are potential determinants of the severity of violation of the light attraction regulation. Consequently, the study further strengthens the need to consider these factors in fishery management decisions.

From the empirical estimations, it has been found that the individual discount rate is positively related to both the violation decision and the severity of violation, with relatively high elasticity coefficients. The high discount rate could be an indication that the fishers are credit constrained due to imperfections in the credit market. Any policy that addresses such imperfections in the credit market is likely to reduce both the severity of violation and also discourage some fishers from violating the regulation.

The risk and severity of punishment are significant in explaining the decision to violate the regulation and the severity of violation given that the individual violates the regulation, with the risk of punishment having a much stronger effect. The risk of punishment is measured by the perceived instantaneous conditional probability of detection and the severity of punishment is measured by the expected fine. Consequently, the fishers could be discouraged from violating the regulation or those who violate will decrease the severity of violation if enforcement effort and/or the penalty increase. Furthermore, younger fishers are more likely to violate the regulation than the older ones, all other things being equal. However, among those who violate the regulation, the older ones have higher severity of violation of the regulation than the younger ones. Consequently, the fishery department should direct more resource to targeting the middle-aged fishers. In addition, the extent to which a fisher thinks the regulation is unfair influences his decision to violate or not, while for fishers who are in violation, the more they think the regulation is to protect the stock, the higher their severity of violation.

Also from both empirical estimations, the fisher's perceived social pressure, measured by his perception of the proportion of the fishers who violate the regulation, is positively related to both the severity of violation and the decision to violate the regulation. Finally the size of the fishing boat which is a proxy for fishing effort, is positively related to the severity of light attraction regulation. The fishery department should therefore direct surveillance to bigger boats.

6. References

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APPENDIX

Table 1. Descriptive Statistics of Variables for the Estimations

Variable	Mean	SD
Probability of detection	0.247	0.201
Expected fine	13.643	16.308
Discount rate	1.180	0.616
Social pressure	0.594	0.234
Age of skipper	40.596	10.634
Education (=1 for at least primary)	0.591	0.494
Size of boat	39.357	19.077
Reg. is to protect stock (5=strongly agree, to 1=strongly disagree)	4.063	1.281
Regulation is unfair (5=strongly agree, to 1=strongly disagree)	2.252	1.345
Dependents	8.165	4.733
Belongs to *Susu* group (=1, and 0 otherwise)	0.278	0.450
Wealth (100's)	42.896	99.153
Ownership	0.461	0.501
Crew	12.555	6.983
Violate the regulation (=1, and 0 otherwise)	0.435	0.498
Replacement cost of light equipment	1001	503.887

Source: Author's survey data 2007

Table 2. Estimated Logit Model for Violation of Light Attraction Regulation

Variable	Marginal effect		Elasticity
	Coefficient	**SE**	
Predicted probability of detection	**-9.674**	(3.553)***	**1.256**
Expected fine	**-0.024**	(0.017)	**0.159**
Discount rate	**0.845**	(0.470)*	**0.530**
Social pressure	**3.386**	(1.404)**	**1.103**
Age of Skipper	**-0.108**	(0.047)***	**2.327**
Education (=1 for at least primary)	0.056	(0.625)	
Regulation is unfair (5=strongly agree, to 1=strongly disagree)	**0.848**	(0.289)***	**1.044**
Dependents	**0.134**	(0.072)**	**0.580**
Belongs to *Susu* group (credit association)	-1.078	(0.673)	
Wealth	0.002	(0.004)	
Number of observations (99); Pseudo R-Squared 0.45			

** implies significant at 5%; and *** implies significant at 1%. Robust standard errors are in parentheses.

Table 3. Estimated Supply of Violation of Light Attraction Regulation using Ordinary Least Square (OLS) and Maximum Entropy Leuven Estimator (MELE)

Variable	**OLS Estimates (Robust SE)**		**Bootstrapped Standard Deviations (SD)**		
	Coefficient	**SE**	**Coefficient**	**SD**	**Elasticity**
Probability of detection(a)	-1.389	**(1.739)**	-1.201	(**0.494**)	**0.196**
Expected fine	-0.026	**(0.007)*****	-0.009	(0.037)	0.091
Discount rate	0.467	**(0.174)*****	0.935	(**0.345**)	**1.245**
Social pressure	2.239	**(0.540)*****	2.019	(**0.526**)	**1.393**
Age of Skipper	1.050	**(0.490)****	3.103	(**0.352**)	**3.098**
Reg. is to protect stock (5=strongly agree, to 1=strongly disagree)	0.080	(0.084)	0.463	(**0.187**)	**1.636**
Size of boat			0.017	(0.012)	0.732
Constant	10.199	**(1.771) *****			
Observations = 48	**R-squared = 0.52; F(6,41)=9.32*****				

Note: The standard deviations were obtained from bootstrap estimates based on 150 replications. ** implies significant at 5%; and *** implies significant at 1%. Robust standard errors are in parentheses. (a) the predicted value of the probability of detection was used in the OLS regression and the observes values were used in the MELE.