CHAPTER FIVE

DETERMINANTS OF NONCOMPLIANCE WITH FISHERY REGULATIONS IN SUDAN'S ARTISANAL FISHERY

5.1 Introduction

The standard DDM described in chapter four is extended in this chapter to introduce broader and more flexible formulations for analysis of the problem of noncompliance with fishery regulations. The main extension of the model is to allow for probability of detection that depends on time. Another feature of the adapted analytical framework is introducing time of detection as a random variable to the model and employing the Cox hazard model instead of the survival hazard function previously used in the literature. The predictions of the adapted analytical model are tested on data collected from cross-section survey of artisanal fishers in the Jebel Aulia Reservoir of Sudan. Factors that determine the probability of violation as well as the extent of violation were analysed, employing the ordered Probit model and count data model, respectively. The econometric model specification, study area and data sources are presented and discussion of findings and results and policy implications of the conducted empirical analyses are provided in this chapter.

5.2 Extensions introduced to the standard DDM framework

In this chapter we introduce two extensions to the DDM of Chapter four. Firstly, although the DDM calculates profits from violation into two periods, namely, before and after getting caught, all previous literature using this model formulates the choice problem to be optimised over an infinite time horizon. The transition between the two periods is therefore not clear. This study assumes that time of detection is a random variable that defines the end of the first period and the start of the second period, which then extends to infinity in period two. Splitting the two periods would then result in an easier distinction between the violation and compliance periods within the time horizon.

Secondly, we adapt the DDM to allow for non-constancy (depend on time) of probability of detection by employing the Cox proportional hazard function, which defines probability of detection to be a function of the multiple of two terms, a constant individual characteristics' function and a time-variant hazard function.

Suppose that the goal of an individual fisher who violates regulations is to maximise his profit from two periods before and after being caught. If the fisher violates specific regulations, we observe a positive rate of violation (i.e. m > 0). According to the DDM adapted in Chapter 4, the profit from fishing illegally in the first period is defined by $\pi(m)$ (illegal profit), where m is the violation rate which increases the gain from violation at a decreasing rate, i.e. $\frac{d\pi_m}{dm} > 0 \& \frac{d^2\pi_m}{dm^2} < 0$. Also as defined in Chapter 4, violation rate is measured by frequency of violation, which is how frequently fishers violate in terms of weeks, months or years. The model assumes that after being caught, the fisher will only fish legally (i.e. m=0) and gets a constant profit net of the fine F and that his profit in the second period is π_0 (legal profit or compliance profit)

Moreover, assume that in absolute terms, illegal fishing is more profitable than legal fishing.

$$\pi(m) > \pi(0) \tag{5.1}$$

As stated earlier, we assume that, in the first period the violator will fish until getting caught at a random time variable τ in the future, given that he has never been caught before. The second period starts from the random time τ when the fisher is caught and required to pay the fine (F).

Here we have two important assumptions to take into consideration. First we assume perfect selectivity i.e. nets with the legal mesh size can harvest only mature stock, and the one with the illegal mesh size can harvest both mature and immature stock. Second, although violators do generally recidivate because of poverty and difficulty in buying an illegal net (expensive for the fisher to buy another net given his poverty suitation), we assume that the fisher is highly unlikely to recidivate following literature (Akpalu 2008). Not as in chapter 4, in this model we assume that the fisher own only one illegal net. Taking into consideration the same specifications of the profit functions that explained in details in chapter 4.

The fisher's inter-temporal expected profit is accordingly given by:

$$J(.) = max\, E\left\{\int_0^{\tau} e^{-\delta\tau}\ \pi(m)dt + \int_{\tau}^{\infty} e^{-\delta\tau}\, \pi(0)\, dt\ - e^{-\delta\tau}F\ \right\} \tag{5.2}$$

Where, *J(.)* is the value function, *E* is the integral expectation, δ is the discount rate, *m* is the violation rate, τ is the random time when the second period starts i.e. the time the fisher is caught and required to pay the fine *F*. we assume that the violator does not know the exact time of detection, but has information about the probability distribution of time of detection. As in Chapter 4, we specify a continuous distribution of time of detection τ with a probability density function pdf (g(τ)) and cumulative density function cdf (G(τ)) such that g(τ) = dG(τ)/dτ, where $0 \leq \tau \prec \infty$. However in this chapter we assume that the fisher is not a pure-maximising agent, but drives disutility (for example, feeling guilty) that incurs a psychological cost, from harvesting stocks, *s* and x with cost functions *k(s)* and *d(x)* respectively, following Akpalu, (2008). This will make the profit function to be re-specified as:

$$u(m) = \pi(m) - k(s) - d(x) \tag{5.3}$$

Where *k>0*, *d>0* and *d*(0)*=0*, and if the fisher doesn't violate his utility is $u(0, b, p_n, Q_n, E_n, x)$.Under the above assumptions, if the fisher is caught, he pays a fine *F*, which is a fixed amount of money plus the cost of the illegal catch which will be seized immediately. The expected present value of the fine is $\int_0^{\infty} Fg(t)\, e^{-\delta t} dt$

We now assume that the fisherman is maximising expected utility over two periods as follows:

$$J(.) = max\, E\{\int_0^{\tau} e^{-\delta\tau}\ u(m)dt + \int_{\tau}^{\infty} e^{-\delta\tau}\, u(0)dt - e^{-\delta\tau}F\ \} \tag{5.4}$$

Where $J(.)$ is the value function, *E* is the mathematical expectation, δ is the discount rate of each skipper and, τ is the random time of detection. Then, the fisher's objective function is to maximise the expected discounted utility from fishing illegally in the first period and legally after getting caught, subject to the survival time (the details of in between calculations from 5.4 to 5. 5 are presented in Heading 1. Annexure B).

$$J(m) = \left\{\frac{u(m)}{\delta} - \left[\frac{u(m) - u(0)}{\delta} + F\right] Ee^{-\delta\tau}\right\} \tag{5.5}$$

The interpretation of this equation is important. The first term of equation (5.5) is the discounted expected benefits of illegal fishing for an infinite time horizon, and the second part (between the brackets) illustrates the penalty that the violator should pay when getting caught, including the illegal gain plus the fine and the disutility the fisher gains by committing the violation. The last term ($e^{-\delta\tau}$) stand for the proportion of time spent fishing legally. That means that if the fisher gets caught, he will end up benefiting only from legal gains.

Then the goal of a violator is to maximise the value function (equation (5.5)) subject to survival time or the probability of detection. While the previous literature assumes a constant probability of detection (doesn't depends on time), this study adds a new formula for the survival time that makes it non-constant, as explained in detail in the following section.

5.2.1 Specification of probability of detection function

Probability of detection is very important and has been limited so far to situations where independence of length of time to detection is assumed and with lack of clarity on factors that determined the probability of detection in the main deterrence model. In this chapter these assumptions are relaxed to allow for a more flexible model. There are plausible reasons to believe that the probability of detection varies over time. Non-constancy of probability of detection could be due to factors beyond the control of violators. For instance, the probability of the violator being caught is small in an artisanal setting but higher when the fishing industry is highly commercialised. Other sources of non-constancy of probability of detection include violator's attitude towards the risk of arrest that varies over time because of age or simply luck or any factor that is assumed to make the hazard rate change over time.

While some attempts have considered influences of probability of detection to vary with the violation rate m but still independent of time (Leung, 1991), so far in the literature, the probability of detection function has been modelled as constant over time. Accordingly influences of important factors were not explicitly entered in the supply of offences function of the deterrence model. This study modifies previous specifications of the hazard function to allow for better understanding of influences of factors determining noncompliance by relaxing key assumptions.

To relax the assumption of constancy of probability of detection, we adopt the Cox's proportional hazard model (CXPHM). This model is mostly used in survival analysis (Cox, 1972) commonly applied to analysis of data in different fields of sciences such as medicine, environmental health, criminology, and marketing (Jenkins, 2005; Lee and Go 1997). The said model is particularly popular in medical sciences when measuring the survival of patients who encounter serious diseases. This study used the CXPHM to define probability of detection (equation 5.6).

$$\mathrm{H}(\mathcal{T}, m, v, n) = \mathcal{B}(m, v, n) h(\mathcal{T})$$

$$\Pr(\mathcal{T}, m, v, n) = \mathcal{B}(m, v, n) h(\mathcal{T}) \qquad 0 \leq \mathcal{B} \leq 1 \textit{ and } \frac{d\beta}{dm} > 0 \qquad (5.6)$$

The right-hand side includes two hazard functions, the first $\beta(.)$ is the individual-specific hazard function, which does not depend on τ , whereas the second $h(\tau)$, which depends on time but not on β factors, is the baseline hazard function. The latter function is the one which determines if the hazard rate is constant, decreasing or increasing (if we use a Weibull distribution for example) as will be explained more in the following sections. The individual hazard function $\beta(.)$ is linearly related to the probability of detection and increases with violation (the crime rate m) and decreases with the enforcement (n) and evasion activities (v) as cited in the literature (Charles *et al*., 1999). This is a special important implication is associated with the Cox proportional hazard because the baseline hazard function can accommodate constant and inconstant time, while the individual hazard function is linearly related to probability of detection. The proportional hazard rate is specified as: $h(.) = \frac{g(m,v,n,\mathcal{T})}{1-G(m,v,n,\mathcal{T})}$ then, we linked this proportional hazard rate with probability of detection specified in equation 5.6 (CXPHM) in order to define the density function with the following general expression (see Heading 2-Annexure B for more details):

$$g(\tau, m, n, v) = \mathcal{B}(m, v, n)h(\mathcal{T})\mathrm{e}^{-\mathcal{B}(m,v,n)h(\mathcal{T})} \tag{5.7}$$

Most of the literature in survival analysis that uses the Cox proportional hazard rate uses exponential distribution because it is easy to implement and interpret. However, according to Bender *et al.* (2005) this assumption does not generate realistic survival time in real life. The most frequently used distribution for survival time is the Weibull distribution (Lee and Go, 1997). Using this type of distribution will make the baseline hazard decrease or increase over time according to the factors mentioned previously (Bender *et al.*, 2005). This modified modelling of probability of detection also makes the previous specification to represent one of the three versions of this formulation, since the new model accommodates situations of constant and non-constant probability of detection

The introduction of the time of detection in equation (5.5) into the value function, gives the following violator's maximisation problem that depends on time:

$$J(m) = \left\{\frac{u(m)}{\delta} - \left[\frac{u(m) - u(0)}{\delta} + F\right]\int_0^{\infty} g(\mathcal{T}, m, v, n)\ e^{-\delta\mathcal{T}}\,dt\right\} \tag{5.8}$$

So the net gain from violation is the expected discounted illegal fishing minus the discounted expected penalty. The last term represents the discounted density of time of detection which is the function of explanatory variables (m, v, n).

For simplicity, the last term of equation (5.8) will be replaced by the following formula throughout the text.

$$D(\tau, m, n, v) = \int_0^{\infty} g(\mathcal{T}, m, v, n)\ e^{-\delta\mathcal{T}}\,dt \tag{5.9}$$

D is the discounted density of the detection time. The discounted density function that is used as the probability of detection in this model can take different distribution functions that give the flexibility of addressing the three possibilities of constant, increasing and decreasing probability of detection by using a Weibull distribution, as example.

Based on literature the following hypotheses are advanced (see Heading 3 Annexure B for the effect of the discount rate)

$$\frac{dD}{dm} > 0; \ \frac{dD}{dv} < 0; \ \frac{dD}{dn} > 0; \ \frac{dD}{d\delta} < 0 \qquad (5.10)$$

Substituting equation (5.9) into the value function, gives the final specification as follows:

$$J(m) = \left[\frac{u(m)}{\delta}\right] - \left[\frac{u(m) - u(0) + F}{\delta}\right] D(\tau, m, n, v) \qquad (5.11)$$

The optimal level of violation is obtained from the first order conditions by differentiating the objective function with respect to *m* to decide on the optimal amount of *m* that maximises the profit through the optimal path. Then the supply of offences function is given by:

$$m^{*} = m(F, \delta, n. v, B) \qquad (5.12)$$

Where *n* stands for enforcement, *F* is the fine, δ is the discount rate, *v* is evasion activities and the perception variables that affect disutility from violation and socioeconomic characteristics of the fishers, such as years of experience and number of crew per boat directly affects the profits and costs of harvest are included in the vector *B*. Other variables include normative factors such as peer pressure which is measured by the perception of the number of violators in the community. This pressure is believed to motivate fishers to increase the rate of violation, following the findings of a number of studies revealing the importance of normative factors for enforcement of regulations (Akpalu 2008; Eggert and Lokina 2010; Hatcher and Gordon 2005; Sumaila *et al*. 2006; King and Sutinen 2010). However some parameters such as prices and cost are incorporated in the constant term of the regression model since they are common for all the skippers (Akpalu 2008).

This extended model is believed to be more flexible as the new specification of probability of detection function introduces to the DDM new variables for the supply of offences function. These are evasion activity and enforcement that have not been included in this model before. This implies that the model can be reformulated to have two control variables m and v. In such case the violator will seek to choose the optimal combination of these two variables. Thus, a useful extension of the DDM is to consider the trade-off between these two choices and possibilities of substitution.

The modified DDM can be used to empirically simulate influences of key determinants of compliance under alternative formulations. For example, the discounted density function that is used to model probability of detection in this study can assume different distribution functions, which allows for the three possibilities of constant, increasing and decreasing probability of detection employing the Weibull distribution. Therefore, simulation and sensitivity analyses can be performed and outcomes compared under the three situations. This may be implemented through maximising the deterrence model in equation (5.11) subject to the proportional hazard equation (5.6) on any optimization algorithm.

Moreover, regression analysis can be employed to empirically measure influences of identified determinants of probability of detection as demonstrated in medical and criminology fields applications of the Weibull proportional hazard regression model (Bender *et al*., 2005; Lee and Go, 1997; Bodenhorn and Price, 2009; Brempong and Price, 2006; Maddan *et al.*, 2008). Applications of the model developed in this study are not limited to the fishery case but can be generalised to management and regulation of other natural resources such exploitation of common property forest, water and grazing lands and hunting of wildlife.

The following section explains the empirical application of the model based on data from a survey of artisanal fishers in JAR of Sudan.

5.3 Empirical applications of the adapted model to non-compliance with regulations in Sudan

The above model is specified and empirically estimated to analyse noncompliance with fishery regulations among Sudan's artisanal fishers. The empirical analysis intends to achieve two objectives. The first purpose is to study factors that influence the choice between violation categories (which type of violator groups to belong to) and the second is to analyse determinants of the rate of violation (intensity) among violators. This is expected to provide useful information on the number of violators, classified into violation groups (NV, OV, CV), and to further determine why fishers choose to belong to different violation categories and to specify the determinants of extent of violation within violators.

Various models have been used to pursue such objectives. Binary Logit and Probit models have been employed to study determinants of the decision to violate or not. However these models have been criticised in the literature as giving limited information about violators (King and Sutinen, 2010). Moreover, binary specifications such as the Heckman selection and hurdle models are not suitable for this study because our sample does not support efficient estimation and the dependent variable is specified as a discrete variable (Kennedy, 2003). Ordered choice models are more suitable when the dependent variable is measured with data of ordered nature.

However, ordered models are not relevant when estimating the extent/intensity of violation within violators. To analyse extent of violation, we choose to employ count data models, which measure how frequently an event happens within an interval of time, as most relevant for the case of this study. Since in this case we are interested in violators only, the Zero Truncated Poisson (ZTP) distribution is employed as the most suitable among commonly used count models. Nevertheless, this model is known to violate the over-dispersion assumption that characterises count data (variance of occurrences exceeds their mean). A generalised version of this model, the Zero Truncated Negative Binomial model (ZTNB) was developed to overcome this problem and is known to give more accurate results over the famous Poisson model (Kennedy, 2003; Long, 1997 and Wooldridge, 2000; Cameron and Trivedi 2005/2009).

Two empirical models are accordingly employed to implement the intended empirical analysis. The ordered Probit model is used to achieve the first objective and the negative binomial model is employed to analyse determinants of the intensity of violation among violating fishers (second objective).

5.3.2 Estimating the determinants of the choice to belong to one of the violator groups

This chapter follows Eggert and Lokina (2010) typology of fishers which distinguishes three groups of fishers; non violators, occasional violators and chronic violators, and our approach also follows the work by Hatcher and Gordon (2005). The dependent variable Y^* is the latent variable measuring the degree of violation, and which has an ordered nature that justifies the use of ordered maximum likelihood for estimating model parameters, and hence our choice of the ordered Probit model (OPM) for analysing determinants of the choice to belong to one of these three fishers' typologies. The general form of the OPM is specified as:

$$Y^* = X'\beta + \mu \qquad (5.13)$$

Where Y^* is the non-observable latent variable and Y is its observed counterpart; X is a vector of explanatory variables assumed to influence the choice to belong to one of the three violator categories; β is the vector of parameters to be estimated; and the error term u is distributed as standard normal (Long 1997; Green 2000). Y is only observed when the latent variable Y^* takes only three values $(0,1,2)$. These values range from $Y= 0$ for non-violators (NV), $Y= 1$ for occasional violators (OV), and $Y= 2$ for chronic violators (CV).

Eggert and Lokina (2010) employed a frequency of violation index based on number of months a fisher has violated to classify fishers into the said three categories of fishers' typology. To implement this, cut-off point to separate violators into OC (1-10 months of violation) and CV (11-12 months of violation) are specified according to the information provided on numbers of months of using legal and illegal nets. We also followed the more behavioural choice variable of type of fishing equipment owned/used the previous year as suggested by Eggert and Lokina

(2010). Fishers are accordingly classified into NV, OV and CV based on their initial choice to use only legal nets (NV), only illegal nets (CV) or in both legal and illegal nets (OV)[7]. Though we expected the skippers to give information about violation rate in continuous time, they argued that it is easier for them to answer in discrete time (number of months).

We assume that the latent variable Y* can be described by a normal distribution, so that

$$\Pr(Y = z) = \Phi(-\beta' X) \tag{5.14}$$

z = 0 if fisher owns only legal nets (NV)
= 1 if fisher owns both legal and illegal nets (OV)
= 2 if fisher owns only illegal nets (CV)

The latent variable is related to the observed variable as follows:

$$Y = 0 \text{ if } Y^* \leq 1$$
$$=1 \text{ if } 1 < Y^* < 11 \tag{5.15}$$
$$= 2 \text{ if } Y^* \geq 11$$

For interpreting model results marginal effects are calculated as given by:

$$\frac{d\Pr(Y=z|x)}{dX_k} \tag{5.16}$$

The marginal effect of factor k is then the slope of the curve relating X_k to $\Pr(Y = z|x)$, holding all other variables constant. In other words, for a unit increase in explanatory variables, the

[7] These numbers are not specified arbitrarily, however, we have cross-checked this behavioural rule criteria of classification with a similar typology, based on data we collected on frequency of violation in months, as in Eggert and Lokina (2010). The two classification systems produced perfectly matched typologies of fishers.

probability of the dependent variable can increase or decrease according to the sign of the coefficient β (Cameron and Trivedi 2005/2009; Kennedy, 2003). We found that, the fishers' situations including fishery typology, socio economic and normative factors in Sudan hardly change due to inefficient institutions. Therefore, we assume that these factors will remain the same over time. This supports the idea of asking about the previous year violation's violations to be reported for the current year.

5.3.3 Estimating the determinants of the extent of violation within violators

To estimate how frequently violation occurs within the year, the ZTNB model is estimated, where the dependent variable *y* assumes a range of values of between 1 to 12 months of violation. This means that the model is truncated at zero. Then the conditional probability of observing *y* events given that *y* > 0 i.e. the probability that fisher violated given that NV are not part of the sample is computed with the law of conditional probability is:

$$\Pr(y_i \,|y_i > 0\,, x) = \frac{\exp(-u_i)u_i^{y_i}}{y_i\,![1-\exp(-u_i)]}\,, \qquad y = 1, 2, \dots, 12 \qquad (5.17)$$

Since zero counts are excluded, value is increased by the inverse of the probability of a positive count (Long 1997):

$$\mathrm{E}(y_i \,|y_i > 0\,, x) = \frac{u_i}{[1-\exp(-u_i)]} \qquad (5.18)$$

u_i is the predicted number of months the fisher violates (probability of given number of months of violation, u_i = 1, 2,..., 12), conditional on explanatory variables (covariates) X_i. A truncated negative binomial model is estimated by modifying the likelihood function (Long 1997) as follows:

$$\mathrm{L}(\beta\,, \propto |\mathrm{y_i}\,, x) = \prod_{i=1}^{N} \Pr(y_i \,|y_i > 0\,, x_i) \qquad (5.19)$$

Generally, the model is estimated by the discrete effect method holding variables at their mean. This model estimates the influence of determining factors on the frequency of violation among violators. The results of this model will be compared with the factors that determine the choice to belong to the middle category since this is the only group that has a great rate of variation.

5.4 Study area and sources of data

To conduct the intended analysis, data were collected through a survey of fishermen from JAR, on the White Nile south of the Jebel Aulia Dam in Khartoum State (Figure 2.3 in chapter 2). Fishers in the study area use mesh sizes as small as 2 cm, targeting small catch that is sold fresh or dried for further processing for own subsistence use later. The population included all skippers in Khartoum state who use gillnets. From this population, a random sample of 241 skippers, constituting approximately 30 % of the total number of boats in the area, were surveyed between February and May 2010. Samples were selected from five survey sites with adequate spatial spread across all landing sites on the White Nile between Khartoum city and the dam. Sampling fractions were allocated to the different survey sites proportional to size of population in the site and then randomly selected from a prepared sampling frame showing lists of fishers willing to be interviewed compiled by the site chief.

The sample was collected randomly from five landing sites because of the high homogeneity of the population in all landing sites. The sample was initially 250 and after data cleaning, we managed to get 241 valid questionnaires. These landing sites are, namely, Kalaklat, El Fiteh, Taweel, El Marsa and south of the Dam.

A structured questionnaire was developed and pre-tested on the different sample of population before administering the main survey. Surveyed fishers were assured of the academic nature of the study being part of a PhD degree research at the University of Pretoria and that the survey has nothing to do with the government or the fishery department in Sudan. The final questionnaire was administered to each of the skippers separately in direct face-to-face interviews. The questionnaire collected information on demographic characteristics (e.g. education and experience) of fishing households, types of fishing nets used and number of fishing crew, skipper's perception of the mesh size regulations, violation rates, and how frequently nets were used during previous year. Other questions covered fishers' opinions on current regulations, whether they experienced any arrests, their interaction with the police and managers, and what evasion measures they used to avoid being caught. Respondents were asked about the previous year to maximise accuracy and minimise an expected bias of caution against providing the current year's information on using unlicensed nets.

The questionnaires were administered by post-graduate students from the University of Juba and chief fishermen from the area who are highly trusted by all the fishers. Each fisher was interviewed alone and a meal (equivalent to 4 US$) was provided to the fisher to compensate for their time. They were asked about previous years' violations to maximise the accuracy and reduce the bias that might occur if they were asked to tell the truth about their own current violation rates.

5.5 Model variables and econometric estimation

To establish fishers' typologies, the surveyed population were asked about the type of net they own/use. Those who indicated that they own only legal net sizes were classified as non-violators and those who only owned illegal nets as chronic violators. Occasional violators are those fishers who owned both legal and illegal nets. Violation rates were measured by asking fishers about how frequently they have used an illegal size net in the past year in number of months (a frequency of between zero and 12 months, where zero indicates no violation and 12 stands for violating the whole year). This information was used to classify fishers into categories of violators. The produced typologies corresponded perfectly to the classification of fishers into NV, OV and CV based on type of net owned (used) information. We found that it is easier for the fisher to give information in number of months rather than days, which implies discrete distribution of the months of using different types of nets.

Although the majority of the fishers belong to the middle group, the number of chronic violators is found to be very significant, unlike in the available literature. The mean age of the skippers is 47 years, with a minimum of 17 years and a maximum of 80 years. The age variable is divided into four categories according to respondents' ages, and results show that younger skippers are more likely to violate. It seems that violators have a higher number of dependents, since 63.1 % of OV and 73 % belong to the household category of 7–12 individuals per family. It is also found that 85.2 % of CV and 68.6 % of OV are not able to buy nets in cash. Results also show higher dependency on fishing as a source of income since 86 % of OV and 94.3 % and only 42 % of NV depend totally on fishing.

Very high violation rates were observed, as only 12.5 % of the respondents reported that they have never violated mesh size regulations (Table 5.1), with 37 % of the violators using illegal small nets all year round (CV) and the remaining 50.5 % alternating between small and prescribed size nets during the year (OV). Although the percentage of violation is high (87.5 %), only 28 % of the violators had been arrested but only 8.5 % of those caught had to pay a fine. It is clear that fishers in the study area have high chances of avoiding a fine, with 3.7 % admitting to bribing as an evasion means. The main evasion measure, practiced by 97 % of violating fishers, is to tie the illegal net to a big stone and let it sink deep when the police is seen, and to try to recover it later when feeling secure. In spite of that, loss of illegal nets remains the biggest cost to violators, as about 70 % of them suffered seizure of nets within the past three years (see questionnaire in annexure C)

The survey gathered information on four categories of noncompliance determinants (Table 5.1). Information on socio-economic attributes such as education level, experience, source of income and number of skipper/boat represented one category of explanatory variables. There is strong evidence in the literature of the significance of socio-economic factors on noncompliance. Information was also collected about a second category of explanatory variables associated with enforcement efficacy and deterrence measures such as: number of times violators met regulation enforcing agents when landing an illegal catch (Agent). This variable assumes to measure probability of detection, followed the suggestion of Kuperan and Sutinen (1998) of estimating probability of detection by one variable measuring the number of times the violator has been seen by the police landing small sized catches or using small meshed nets**.** We coded information recorded in a three-scale measure, ranging from always to seldom and never seen.

To estimate the probability of being fined when caught, fishers were asked about the action taken against them when caught. However, it was not possible to find information in this variable within the current year or last year, so we were forced to ask them if they experienced net seizure in the past three years. If the answer was only net seizure (Action) then paying the fine is bypassed. This category also included information on incentives to violate, such as whether or not a fisher used some evasion mechanism to avoid seizure of net or paying a fine (Evasion). Fishers were also asked if they believe a small mesh net is more profitable than the prescribed size nets (e.g. Advantage on profit from violation) and if they could buy illegal nets on credit or only on cash basis (Credit). This variable is believed to reflect violators' poverty level and hence their discount rate (i.e the discount rate is therefore measured by the ability to pay in cash or credit for their nets). Those who pay cash for their nets were considered to be relatively well-off and hence have a lower discount rate (less concerned about the present).

The third category of explanatory variables included influences of social (ethical) factors on noncompliant behaviour. Information on one such factor was sought by asking fishers whether they perceive their peers' attitude towards violation to be wrong or not (Unethical). A fourth category of noncompliance factors represents fishers' perception of the legitimacy and efficacy of the regulations. Information was collected on four legitimacy variables: if fishers' views were considered in formulating the regulations (Unjust), if small mesh prohibition is fair (Unfairness), if the enforcement in JAR is adequate (Inadequacy), and if a violator can skip detection even if they violate (Ineffective). Previous studies revealed that such factors are important determinants of noncompliance (Eggert and Lokina, 2010; King and Sutinen, 2010 and Sutinen and Kuperan, 1999). Some of these variables had to be dropped (Unfairness and Ineffective) from subsequent analyses due to high correlation with other explanatory variables. Correlation between the remaining explanatory variables (multi-co-linearity) was estimated to be less than 0.54.

Table 5.1: Descriptive statistics of variables included in the estimations

Name	Variable description	Mean/%
Violation rate		
NV	Non-violators (Zero frequency)	12.5%
OV	Occasional violators (1–10 months)	50.5%
CV	Chronic violators (11-12 months)	37.0%
Education	Level of education	2.82
Experience	Years of fishing experience	27.63
Crew	Number of crew per boat	3.14
Income	If fishing is the main source of income (Yes = 1 and No = 0)	77.5%
Agent	Number of time seen by agent when landing illegal catch (0/1)	15.1%
Action	Net seized (No=0, Yes=1)	24.5%
Credit	Ability to pay in credit or cash (Yes = 1, No = 0)	72.9%
Evasion	Net sinking 1/0	80.1%
Advantage	Small net profitable (Yes=1, No=0)	77.6%
Unethical	Peer violation is not wrong (Yes=1, No=0)	56.4%
Unjust	Fishers' views considered in regulation design (No = 1, Yes = 0)	75.1%
Adequate	Enforcement in fishing area is adequate (Yes = 1, No = 0)	70.1%

5.6 Discussion of empirical results

This section shows the results of the econometrics estimation of determinants of violation rate in two sections. First, the model includes all fishers in general and then the marginal effect is estimated to show the determinants for each fisher typology.

The OPM specified above was fitted to the data described in Table 5.1 and estimation results are presented in Table 5.2. As mentioned earlier, our dependent variable is an ordered variable classifying fishers into three typologies: NV, OV, and CV. Error statistics indicate a good statistical fit of the model. Deterrence variables have the expected signs and together with the socioeconomic factors their influences have high statistical significance.

Table5. 2: Estimation results of the ordered Probit model of the probability of violation category

Variable	Coefficient	Standard error
Socioeconomic variables		
Education	-0.220*	0.127
Experience	-0.038***	0.011
Crew	-0.298***	0.115
Income	1.43 7**	0.577
Deterrence variables		
Agent	-0.807*	0.473
Credit	0.734**	0.376
Action	0.982**	0.411
Evasion	5.836***	1.162
Advantage	2.167***	0.601
Ethical variables		
Unethical	0.239	0.327
Legitimacy variables		
Unjust	0.239*	0.327
Adequate	-0.791**	0.360
*Significant at 10 % ;** Significant at 5 % ; *** Significant at 1 %.		
Prob> Chi^2 = 0.0000; Log likelihood = 133.27 No of observations = 241; Pseudo R^2 = 0.431		

On the other hand, except for the social ethical variable (Unethical), influences of enforcement and legitimacy variables were significant. Results suggest that the probability of noncompliance decreases with education level, years of experience, and number of crew employed, and increase with increased reliance on fishing as the only source of income. Results also show that using evasion activity to hide the quantities of illegal catch encourages violation, and violation increases if the perception of fishers that illegal net is more profitable than the legal net.

To measure the effects of influencing factors on the probability of belonging to any of the ordered fishers' categories, we derive measures of marginal effects of one unit change (increase/decrease) in explanatory variables, holding all other variables at their mean levels (Table 5.3). A negative sign indicates willingness of a fisher to leave the group (i.e. discouraging factors) and the reverse holds for a positive sign (i.e. incentive to remain in the same group or increased association with the current position/choice).

The effect of deterrence variables on non-violators is irrelevant since they don't interact with regulators and have not experienced arrests before. However, the only variable of significance that appears to be highly correlated with the probability of compliance is the fact that members of this category of fishers do not use illegal nets and hence do not need to use evasion measures (large negative effect of 48 % of odds).

Among the socioeconomic factors, better education and more years of experience tend to encourage moving to lower violation categories (OV and NV), e.g. discourage chronic violation. High reliance on fishing income has the opposite effect. This is an indication that with better education and more experience fishers are able to diversify their income sources and hence have less dependence on fishing for living. More crew members on same boat seem to discourage chronic violation. This could be due to the relatively higher risk of being caught and fined for a large number of crew and the fact that they can pool resources to afford alternating between legal and illegal nets.

While some deterrence factors have the expected sign for all violating categories (i.e. prevalence of regulation agents and use of evasion measures) effects of others vary between OV and CV. For example, poor violators (access to credit) and higher profitability of illegal fishing seem to encourage higher violation (move from occasional to chronic violators' category).

Table 5.3: Marginal effects of determinants of decision to violate

	Non-violators		Occasional violators		Chronic violators	
Variable	dy/dx	*t stat*	dy/dx	*T stat*	dy/dx	*t stat*
Socioeconomic						
Education	0.0019	0.94	0.321*	1.67	-0.0341*	-1.68
Experience	0.0003	1.08	0.0052***	3.32	-0.0055 ***	-3.38
Crew	0.0028	1.07	0.04670***	2.72	-0.0496***	-2.77
Income	-0.0309	-1.01	-0.1427***	-4.34	0.7136***	3.65
Deterrence						
Agent	0.0049	0.98	-0.1395	1.48	-0.1445	-1.50
Credit	-0.0093	-0.96	-0.9940**	-2.24	0.1088**	2.18
Action	-0.0061	-1.01	-0.1757**	-2.11	0.1818**	2.15
Evasion	-0.4701***	-3.48	0.1329	1.02	0.3372***	8.53
Advantage	-0.0556	-1.37	-0.1925***	-4.71	0.2482***	5.63
Ethical variables						
Unethical	0.0025	0.65	0.038	0.80	0.0412	0.80
Legitimacy						
Unjust	-0.0084	-0.91	-0.0922**	-2.08	0.1007* *	2.01
Adequate	0.0059	0.99	0.2155*	1.93	-0.1314*	-1.95
*Significant at 10 % ;** Significant at 5 % ; *** Significant at 1 %.						

On the other hand, while the act of seizing illegal nets discourages OVs, it seems to unexpectedly encourage CVs. That may be because it is better for them to give up the net than to pay the fine (no cash) or it may be that their nets are rarely seized due to effective evasion. It might also refer to the fact that seizure of illegal nets has actually been internalised by the fishermen who do not comply and counted as part of the cost of over-fishing. Thus they have taken this into account in their optimization problem. Another factor with an unexpected effect on CV is the ethical factor (i.e. believing that peer violation is not wrong). Not considering fishers' views in designing regulations encourages higher violation (from OV to CV), and the belief that enforcement is Adequate provides an incentive for the flexible strategy of moving to less violation categories for both OV and CV i.e decrease frequency of violation.

In order to achieve the second objective of determining the factors that influence the frequency of violation among violators only, the zero truncated negative binomial (ZTNB) model was employed. Results from this model are presented in table 5.4 and are compared to those from the OPM. Some variables (income, credit, advantage, action, and fairness/unjust) share high statistical significance in both models and their signs confirm our OPM results that they all encourage moving from the OV to the CV category, i.e. increasing degree (frequency) of violation (+ve effect in the ZTNB model - Table 5.4).

Table5.4: Determinants of extent of violation within violators.

Variable	Coefficient	T stat
Socioeconomic variables		
Education	0.023	1.30
Experience	0.005	0.40
Crew	-0.001	-0.12
Income	0.43 7***	4.50
Deterrence variables		
Agent	-0.075	1.00
Credit	0.167***	2.85
Action	0.118**	2.04
Evasion	1.78***	7.56
Advantage	0.1231***	2.89
Ethical variables		
Unethical	0.087*	1.79
Legitimacy variables		
Unjust	0.149***	2.61
Adequate	-0.050	-0.94
* Significant at 10 %; ** Significant at 5 %; *** Significant at 1 %.		
Prob > Chi^2 = 0.0000; Log likelihood = -514.38423 No. of observations = 211; Wald chi2(12) = 9443.51		

Similarly the variable Evasion seems to motivate higher violation rates (increased frequency) both within OV category (from 1 to 11) moving to CV status. While not showing statistical significance in affecting the choice to belong to violator categories, ethical beliefs have a significant, positive effect on frequency of violation. That means the community's ethical beliefs have important influences on degree of violation, especially if violation is a common behaviour in the community. This positive influence is expected among the fishing populations especially where poverty is high and violation is very common.

Interestingly, both models show low statistical significance of the effect of an agent factor (measuring probability of detection). This is consistent with other studies' findings, confirming the problem of low probability of detection in developing countries due to the high cost of enforcement and monitoring. In addition, the effectiveness of this measure is also a function of other factors such as evasion activities. Socio-economic factors such as education and experience while having significant influences on the choice to belong to violator groups do not seem to be of significance for how intensive violation is.

5.7 Summary

The standard DDM explained in chapter 4 was modified in an attempt to introduce a broader and flexible model that allows analysing noncompliance with fishery regulations problem by modelling probability of detection as a Cox hazard model instead of the survival hazard used in the literature which in turn implies probability of detection that depends on time. The new modelling of probability of detection introduces to the DDM new variables for the supply of offences such as evasion activity and enforcement that have not been applied by this model before.

The developed model was parameterised and used to analyse determinants of noncompliance with mesh size regulations among artisanal fishers in JAR of Sudan. The studied determinants include both deterrence (detecting and fining) and normative (ethical) factors. High violation rates were observed (87.5 %) with 58 % OV and 42 % CV. Two models were employed in the analysis: the OPM to examine effects of factors influencing the choice of what fishers' category to belong to (NV, OV or CV), and the ZTNM analysed determinants of how frequently violation occurs (extent).

Results show that evasion activities attract NV to violate; education and experience discourage chronic violation; while access to credit and high profitability encourage chronic violation. On the other hand, believing that enforcement is inadequate provides an incentive for the flexible strategy of being OV. More crew numbers on the same boat also discourages violation.

In both choice and extent of violation models, probability of detection (being seen by an agent) was not important as a deterrent. The study results suggest that fishers care more about penalty (seizure of net) than presence of an agent as a deterrent. This is mainly due to corruption and weak enforcement mechanisms, and effective evasion by fishers. This is consistent with widely observed phenomena in developing countries. Efforts to increase efficacy of detection, monitoring and enforcement of regulations and reduce evasion are some of the policy measures to consider for fighting noncompliance.

The study suggests that unless there is better understanding of violators' behaviour and enforcement of severe penalties on violators' noncompliance with mesh size regulations, violation is expected to increase to the extent that fish stocks may collapse in the JAR. It is therefore recommended that future empirical research on fisheries crimes in Sudan and developing countries should incorporate important factors like the discount rate, bribing and evasion activities.

The study also suggests that investment in better education of fishermen, provision of alternative income and employment opportunities outside fishing, access to credit for ownership of legal nets, effective regulation on importation of illegal nets will be necessary for enhancing compliance with mesh size regulations in Sudan. It is also necessary to promote community level organisation and awareness campaigns among fishers about the dangers for future fish stocks of eroding small fish quantities through the use of illegal nets and consequently endangering the social welfare of all.

CHAPTER SIX

SUMMARY, CONCLUSIONS, AND IMPLICATIONS FOR RESEARCH AND POLICY

Though Sudan is considered to be endowed with good fishery resources, the fishery sector contribution to national economy is marginal. The sector nevertheless supports livelihoods of some of the poorest segments of the population in the country in providing food and income and employment opportunities. Like other developing countries the fishery resources in Sudan are over-fished and the situation is bound to worsen with mounting population growth, fast urbanization, and predicted climate change pressures in addition to the increased health awareness of the nutritional value of fish building increased demand for fish in the future.

Inland waters of Sudan contribute 88.3 % of total fish potential production. The fishery sector however is believed to perform poorly. The sector poor performance is attributed to lack of strategic planning, serious institutional and governance weaknesses due to low commitment of financial and human resources, and high poverty levels among small producers.

Jebel Aulia reservoir is the main supplier of fresh and processed fish in Sudan, contributing 52 % of the total inland catch in northern Sudan. This reservoir is endowed with ecological factors that enable it to produce high sustainable yield of fish for the coming future. Proximity to the capital city Khartoum, the major urban concentration and centre of consumption, gives this area an economic advantage. The area is believed to face a pressure of over-fishing, however. A number of factors have been reported to be behind this over-fishing pressure. Among cited reasons are: increased use of illegal fishing gear, smaller than prescribed mesh sizes, deficiencies in law enforcement, leading to loss of species diversity and heavy pressure on remaining breeding grounds and reduction of natural regeneration. Noncompliance with fishery regulations especially the use of small mesh sizes, which hinders fish reproduction, is expected to increase in the future.

Poor enforcement of fishery regulations is attributed to lack of effective institutional structures to carry out this task**.** The Fisheries Department responsible for enforcing fishery regulations faces significant difficulties for administering the wide spread of a large number of fishers along the very extensive banks of the White Nile River, making it hard to monitor these fishing activities. It also receives little support from other related institutions such as the police and the judiciary**.** These difficulties in managing the resource encourage illegal fishing, especially the use of undersized meshes, which is spreading rapidly throughout the inland waters of Sudan.

Accordingly, policy makers need to evaluate the extent of violation, understand and give more attention to fishers' behaviour and reasons for not complying with mesh size regulations in order to achieve an adequate level of compliance and save this important renewable source from collapse.

Some studies have been undertaken on the problem of over-fishing in the study area but haven't provided adequate information on how to deal with the problem. Few Food and Agriculture Organisation (FAO) and governmental reports agree that the resource is over-fished and it is time for the government to intervene. However, none of the studies have attempted to look at the problem of illegal fishing and incentives for noncompliance with mesh size regulation.

This presents an important limitation as a deep understanding of how fishers behave and their reactions to regulations is very crucial to tackle the problem. In addition, none of the studies applied a fishery economics approach to explain noncompliance in fishery management. Most of the studies have focused on the biological aspects and limited socio-economic information about fishers, food processing and other aspects of fishing. This is a clear indication of a serious neglect of the fishery sector that might result in huge losses to the country and livelihoods of fishers.

Other studies show that noncompliance with small mesh sizes is very common in Africa. For example, Akpalu (2008 and 2009) and Eggert and Lokina (2010) found that the use of small mesh size seriously affected the fishery resources in Ghana and Tanzania, respectively. However the study by Eggert and Lokina (2010) was limited to the application of static deterrence model. On the other hand Akpalu (2008), though takes into consideration the dynamic nature of the problem, has not addressed the importance of measuring extent of violation which would improve our understanding of the severity of the violation. The later study is also limited to probability of detection that dosnt depend on time assumptions of the dynamic deterrence model (DDM).

Many studies employed deterrence models either in static or dynamic formulations. The static deterrence model assumes that the violator faces a one-period decision problem of maximising expected utility. The static model assumes that fisher has a fixed amount of time on which he spent some amount on violation. The fisher faces one-period binary decision of either to obey or violate specific regulations. This ignores the dynamic nature of the detection time, the repeated nature of the crime and discounting the future benefits. It also ignores the fact that violators might get away from being detected and therefore wants to know how much money will accumulates through time from violation. On the other hand, the two periods dynamic deterrence model assumes that violators enjoy incremental profit in the first period from fishing illegally, get caught at random time, punished and forced to behave legally thereafter. However so far the DDM measures violation rate by intensity (measured by composite index of the small mesh size) rather than frequency of violation (measured by number of months fishers violate in the time horizon). No study has yet used frequency as a measure of violation rate in a dynamic formulation in spite of the proven advantages of using frequency. Another important gap is that, the DDM has been limited to the case of a constant hazard rate case, which assumes that the probability of detection is independent of the length of time to detection.

The present study attempted to address these gaps in a two ways. First, the standard DDM was adapted to use frequency rather than intensity measures to represent violation rates in analysing determinants of noncompliance with fishery regulations. The study then compared analytical results from the adapted model with findings of static and dynamic models using intensity rather than frequency measures of violation. Second, this study extended the DDM to allow for inconstancy of the detection time, which in turn implies inconstancy of the discount rate.

Introducing frequency as a measure of the violation rate allowed construction of a typology of fishers based on their level of violation as: non-violators (NV), occasional violators (OV) and chronic violators (CV). Further, the factors that influence compliance with mesh size regulations were identified and included in the offence supply function. We further applied the method of comparative static to explore the effects of various factors on the frequency of violation using the implicit function theorem differential rules. The model allowed analysis of the influences of determining factors such as the size of fine, probability of paying the fine and the discount rate, cost of illegal net and average price of the mixed catch on the noncompliant behaviour of violating fishers.

Findings from this model reveal that a greater expected fine and probability of paying the fine discourage violation whereas a higher discount rate is a motive for violation. Regarding the effect of increase in the cost of illegal nets, an interesting result shows that in order for this policy to deter violation the incremental risk of being caught should be less than the average expected gains from not violating per violation attempt. Higher prices of illegal mixed catch, increases and attract more frequency of violation.

Analytical results derived from our adapted model were compared with findings of other studies employing both static and dynamic formulations. Dynamic formulations have important advantages over static models as they could control for the effects of key factors such as discounting the future, costs and prices. Analytical results derived with the extended DDM that uses frequency measures confirm findings of empirical DDM employing intensity measures for effects of key factors such as probability of paying fine (enforcement), level of fine and discount rate. Employing frequency instead of intensity could also sign the indeterminate effects of price of and income from illegal fishing and change in probability of detection.

Until now, the standard DDM has been limited to the case of a constant probability of detection which assumes that the probability of detection is independent of the length of time to detection and the factors that determined the probability of detection lacked clarity in explanation. As probability of detection is considered to be a salient issue of compliance, better understanding of how this function behaves is very important. The second important contribution of our study is extending the standard DDM to relax the assumption of fixed probability of detection. This is because there are good reasons to believe that probability of detection depends on time. Inconstancy of probability of detection could be influenced by factors beyond the control of violators. For instance, the probability of the violator being caught is small in an artisanal setting but higher when the fishing industry is highly commercialised. Other sources of inconstancy of probability of detection include violator's attitude towards the risk of arrest that varies over time because of age or simply luck or any factor that is assumed to make the hazard rate change over time.

Employing the Cox's proportional hazard function to our model accommodated the hypothesis of inconstant probability of detection and the results provided better explanations of factors influencing probability of detection. Extended model findings confirm those of earlier studies and introduce, for the first time, two important variables to the supply of offence function, namely evasion and enforcement efforts. The new modelling of probability of detection makes the previous specification to be only one version of the three versions of the adapted model, since it accommodates situations of constant and inconstant probability of detection (if we use a Weibull distribution).

Applications of the modified model developed in this study is not limited to the fishery case but can be generalised to management and regulation of other natural resources such exploitation of common property forest, water and grazing lands and hunting of wildlife. Regression analysis can be employed to empirically measure and test hypotheses on influences of identified determinants of probability of detection as demonstrated in medical and criminology fields applications of the Weibull proportional hazard regression model.

The present study tested the extended DDM using data from a survey of 241 fishers in the JAR area in Sudan. Study results showed that the majority of fishers in the northern part of JAR are violators (50.5 % occasional and 37 % chronic) and only 12.5 % do not violate. The high violation rate especially the high number of chronic violators indicates severity of the problem. Data was collected on different socioeconomic categories, such as education and source of income, as well as deterrence factors explaining the interaction between violators and regulators. Social and legitimacy aspects were also included, as well as the community's opinion about violation and their perception of regulations

The extended model was applied to examine influences of both deterrence factors (e.g. detection and fining) and normative factors (e.g. peer pressure) on violation by fisher typology. It further identified the factors that influence extent of violation by measuring how frequently violation occurs among violators. The model was empirically estimated as an Ordered Probit model, which enabled analysis of factors that affect the decision to belong to each group of violators: NV, OV or CV. The study further employed the zero truncated negative binomial model to specify the determinants of extent of violation among violators.

All the factors mentioned (deterrents, demographic and legitimacy variables) were found to be significant determinants of the choice to be an occasional or chronic violator, with the exception of social and probability of detection variables. The implication of no significance of probability of detection is that when fishers decide to violate, they put more value on the gain from violation than the penalty paid as punishment of the violation if caught. Higher levels of education appear to discourage violation because it increases the chances of getting employment and hence another source of income other than fishing. If fishing is the only source of income and if fishers' perception about enforcement and regulations is not good, these could encourage violation.

The zero truncated negative binomial model was employed to analyse and measure effects of determinants of the degree of violation within the group of violators. Results from this model are compared to those from the Ordered Probit Model. The results suggest that fishers care more about penalty (seizure of net) than the presence of an agent as a deterrent. This is mainly due to corruption and weak enforcement mechanisms and effective evasion by fishers, a result consistent with widely observed phenomena in developing countries. Efforts to increase efficacy of detection, monitoring and enforcement of regulations and reduce evasion are some of the policy measures to consider for fighting noncompliance.

The study suggests that unless there is better understanding of violators' behaviour and enforcement of severe penalties on violators, non–compliance with net size regulations is expected to increase to the extent that fish stocks may collapse in the JAR. It is clear that immediate government intervention is crucial and important policy reforms are urgent to save the fisheries of JAR from collapse. It is therefore, important that future research on fishery crimes in

Sudan and the developing world must incorporate and study the effects of important factors like social discount rate that gives information about the extraction rate of the resource, in addition to bribe and evasion activities factors.

The study also suggests that investment in better education of fishermen, provision of alternative income and employment opportunities other than fishing, improvement of the credit market for ownership of legal net and effective regulation of importation of illegal nets will be necessary for enhancing compliance with mesh size regulation in Sudan. It is also necessary to promote community level organisation and awareness campaigns among fishers about the dangers for future fish stocks of eroding small fish quantities through the use of illegal nets and consequently endangering the social welfare of all fishers.

Among the limitations of the study is the focus on only the northern part of the JAR in Khartoum state. As stated earlier the effects of other important explanatory variables need to be analysed. Fishers' difficulties with understanding some concepts like probabilities and perceptions about their opinion on regulations and enforcement measurements forced their exclusion from the model. Information about the study area and fishery in general in Sudan is based on few and unpublished sources due to unavailable data and limited publications.